Designing Low Voltage feeders to meet Quality of Supply specifications for voltage variations

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Prepared for the Faculty of Engineering and the Built Environment

DECLARATION

I declare that this postgraduate dissertation is my own work. All sources that I have used and quoted have been referenced. This work has not been submitted to any other University for any other degree or examination.

______________________ ______________________

Holiday C Kadada Date

DEDICATION

You will always be missed Ambuya.

ACKNOWLEDGEMENTS

"*Consider it pure joy, my brothers, whenever you face trials of many kinds, because you know the testing of your faith develops perseverance. Perseverance must finish its work so you maybe mature and complete, not lacking anything*"

- **James chapter1 verses 2-4 [NIV]**

Sincerest thanks to Professor C.T. Gaunt and Dr R Herman for the support and supervision. Your passion for research is inspiring and infectious.

To my family, I appreciate all the support. I love you very much. See you at Graduation!

Special thanks also to my campus family, Gaunt's children MSc class of 2010/2011.We had some fun times.

ABSTRACT

The provision of electricity has become a global necessity. In the developing world, residential electrification has become a tool for poverty alleviation. Unfortunately connecting residential customers to the grid, particularly in the low income communities, is more of a social task as the expected returns from the investment are unlikely to cover the costs to electrify and supply the communities. In such cases it is necessary to not over- or under-design a low voltage (LV) distribution network as this leads to unnecessary capital expenditure.

The main source of uncertainty in designing LV residential distribution networks has been found to be the mode used to model the residential load. Residential electricity demand is a stochastic parameter dependant on the behaviour and occupancy patterns of household occupants. Traditionally the After Diversity Maximum Demand (ADMD), which is in essence and average value of load per household, was used to model load. However, using a singular value to describe the complex random nature of load is misleading. Probabilistic methods have been adopted to model residential load behaviour as these methods are better suited to representing the stochastic nature of the load. The Beta probability function was found to be the best representative function of residential load as its characteristics were reflective of the attributes of residential load.

Studies on pre-existing LV networks in South Africa have found that these networks are operating outside of Quality of Suppy (QoS) regulation. The current QoS guideline of South Africa NRS 048-2 stipulates that 5% of measured supply voltage levels measured during a certain period are allowed to be outside the QoS compliance limits. This means that 95% QoS compliance of supply voltage levels is required for all LV networks. This QoS condition has not currently been worked into the design parameters. If a network is operating out of QoS guidelines a network upgrade is necessary. This research showed that the main source of the QoS violations of these networks was due to the risk levels used to calculate the expected voltage drops during the design stage of the networks. Typically 10% risk is used for voltage drop calculations. This means that a best case of 90% compliance is expected which is outside the 95% compliance limit required by NRS 048-2.

This study focused on two objectives. The first was to derive design parameters that are representative of residential load and can be used to design LV networks that comply with QoS specifications. The second was to define a means or develop a model for LV network designers to distinguish the parameters appropriate for a design, based on the customer class to be electrified.

In this investigation new design parameters were derived that incorporate the 95% compliance limit of NRS 048-2 allowing LV networks built based on the new parameters, to operate within QoS limits. The parameters were derived using residential load data collected in South Africa since the early 1990's. An equation was also derived which allows countries with only ADMD data available to calculate QoS design parameters suitable for their situation.

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ACCRONYMS

ADMD:*After Diversity Maximum Demand*

BPP: *Beta Parameter Plot*

CB:*Circuit Breaker*

CF:*Coincidence Factor*

COV:*Coefficient of Variation*

CPI:*Consumer Price Index*

DSM:*Demand Side Management*

HWC:*Hot Water Cylinder*

IVD:*Iso-Voltage Drop*

kVA:*Kilo Volt Amperes*

kW:*Kilo Watt*

LSM:*Living Standards Measure*

LV:*Low Voltage*

PDF:*Probability Distribution Function*

rms:*Root Mean Square*

Vd:*Voltage Drop*

Vdmax:*Maximum Voltage Drop*

QoS:*Quality of Supply*

1

INTRODUCTION

This report investigates the need for simple, accurate and representative design parameters that comply with Quality of Supply standards to be used in low voltage (LV) residential distribution network planning and design, which will facilitate the construction of economic and reliable networks.

In this report, current LV feeder design procedure is scrutinized and shortcomings are addressed. An alternate way to derive design parameters is described which is expected to curb possible violations of the supply voltage fed to the customers by the Utility.

1.1 BACKGROUND

Electrification is an on-going global practice motivated by different factors. Whether it is for economic, socio-economic or purely social motivations, the provision of electricity has become a necessity. Looking at the developing world, electricity is being used as a tool for poverty alleviation, a good example being the socially based national electrification program being carried out in South Africa, which has proven to be a financially demanding undertaking. A contributing factor to this cost is the fact that the returns expected from electrifying a disadvantaged community do not cover the costs associated with the scheme [Borcher et al, 2001]. Looking at the more financially viable electrification schemes, in the current electrical market, it is important for the power providers to develop optimal network designs that allow them to offer competitive rates to their customers without violating Quality of Supply (QoS) standards.

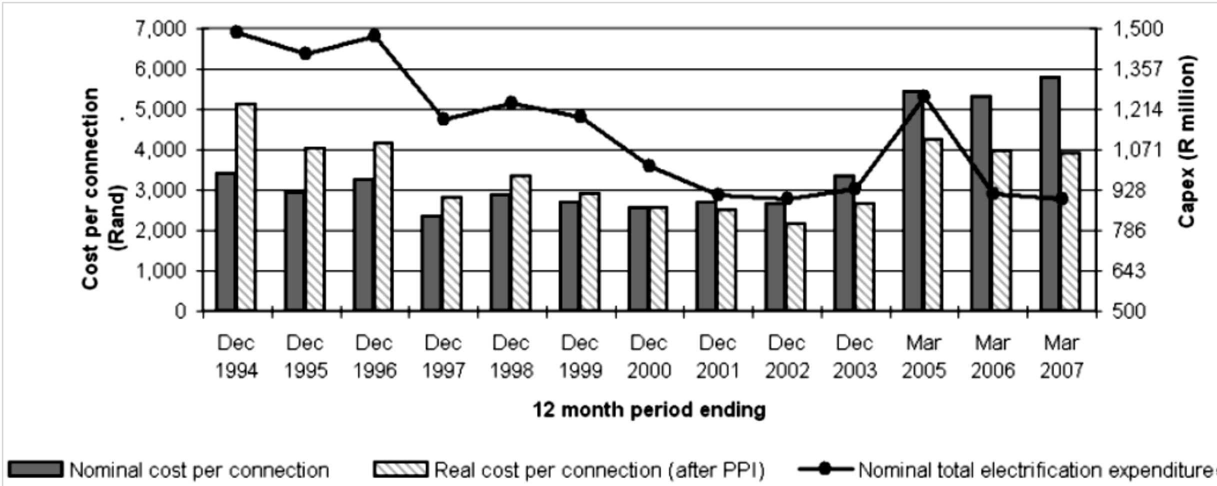


Figure 1.1: Average annual cost per connection and total electrification capital expenditure [Bekker et al, 2006]

A universal problem faced is the connection costs required for building a distribution network. These costs, albeit not the sole expenses, have been described by Khatib [1997] as being the most significant cost contributors in electrification projects. Clearly not an isolated opinion, connection costs have proven to be a major obstacle to South Africa's electrification program increasing significantly since 2001 as shown in figure 1.1. This increase has been reported to be due to the increasing price of raw materials as well as the electrification program moving to sparsely distributed rural communities [Bekker et al, 2008(a)].

The South African guideline document NRS 034-1 [2007] has owed the unnecessary exceedance of connection costs to being due to the overestimation of load, stating that, "*Load estimation for urban or rural domestic consumers is very important in the cost of the electrification system. Overestimation ("safe estimate") will result in overcapitalization, while underestimation results in a poor quality of supply which could lead to expensive reinforcement later*". This observation is shared by Hamadi and Soliman, [2005], who state that "*An extensive overestimation of load demand will result in substantial investment for the construction of excess power facilities, while underestimation will result in customer discontentment*".

These statements by Hamadi and Soliman [2005] and the NRS 034 [2007] task force suggest that the best method of mitigating the connection costs as well as avoiding premature upgrading of LV distribution networks, either to meet an unforeseen magnitude of demand or to achieve the required quality of supply, or both, is to accurately forecast the load expected on the LV network. This is a task within itself, especially when considering long term forecasting, because of factors such as:

- The variable nature of electricity usage of residential customers,
- The growth of load with time,
- Effects of time e.g. time of day, day of week, seasons and holidays on electricity usage,
- And unforeseen developments or demolitions in communities.

The quest to achieve optimum designs is therefore unachievable if precise design parameters, reflecting the expected load, are not available. Lack of such parameters typically generates the otherwise preventable excess capital or running costs. The engineering challenge thus is to produce cost effective and appropriate electrifications networks that conform to the associated financial, technical and political constraints [Herman and Gaunt, 2005].

This thesis will therefore focus on two objectives. The first is to derive design parameters that are representative of residential load, which can be used to design LV networks that comply with QoS specifications. The second is to define a means or develop a model for LV network designers to distinguish the parameters appropriate for a design, based on the customer class to be electrified. The developed model will be generalized so as to make it available to other countries worldwide with different quality restriction and usage patterns from those in South Africa.

1.2 RESIDENTIAL LOAD MODELLING

Carter-Brown et al, [2005], state "*Assumptions for load magnitude are likely to be the largest source of error*" and go on to endorse efforts towards the improvement of load forecasting. A supporting statement that highlights the universal problem faced by designers in achieving optimal distribution network designs would have to be; "*The largest source of uncertainty in LV distribution design is in the modelling of the design load*" [NRS 034-1, 2007].

Leon-Garcia [1994] defines a model as "*an approximate representation of a physical situation. A model attempts to explain observed behaviour using a set of simple and understandable rules. These rules can be used to predict the outcome of experiments involving the given physical situation. A useful model explains all relevant aspects of a given situation. Such models can therefore be used instead of experiments to answer questions regarding the given situation. Models therefore allow the engineer to avoid the costs of experimentation, namely, labour, equipment and time*"

There are various successful methods of load modelling available as reviewed by Swan and Ugursal [2009]. However, the success has been based on models designed from data available at the time of research, the sample size of which in some cases in their review comprised of a few households for a few days in the week. It stands to reason therefore that the accuracy of load models is significantly compromised by the unavailability of accurate, sufficient and relevant data. This leads to planners having to make various assumptions or using parameters from countries that do not necessarily reflect the circumstances in their own situation to compensate for this lack, as was the case in South Africa [Herman, 1992].

The stochastic nature of electricity consumption in the residential sector introduces uncertainty when it comes to the development of any load model, as it is an aspect over which the planner has no control. There are means of limiting electric consumption e.g. using current limiting circuit breakers, load limiting relays, central water heater control, etc [Herman, 1989], but controlling the usage pattern of consumers is not always practical as that would involve a pre-determined timed usage of each appliance owned by the household whether its needed or not. Swan and Ugursal [2009] categorized the available load modelling techniques into two main catergories, top-down and bottom-up illustrated in figure 1.2.

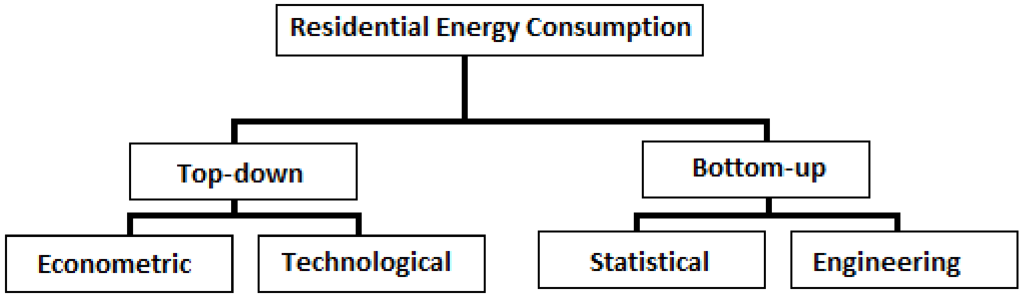


Figure 1.2: Top-down and bottom-up modelling techniques for estimating the regional or national residential energy consumption. [Swan and Ugursal, 2009]

The top-down approach looks at the residential sector as an energy sink which does not allow for much accuracy. Therefore the choice of the most appropriate methods is between the statistical (probability) and engineering (deterministic) models of the bottom-up approach. Deterministic models assume ideal conditions in which the outcome will be exactly the same as long as the input parameters and conditions remain the same. Probability models however work under less idyllic theory. These models work best when examining systems which display unpredictable variations. That is, keeping inputs and conditions the same does not guarantee the outcomes to be similar all the time as in deterministic systems [Leon-Garcia, 1994].

The common problem affecting network planners and designers is modelling the stochastic nature of customer loads [Herman and Gaunt, 2008]. Because of this stochastic nature a probabilistic load model would be the better suited to accurately represent load.

1.3 VOLTAGE REGULATION PROCEEDURES AND QUALITY OF SUPPLY STANDARDS

Voltage Regulation

The calculation of the voltage drop parameter along a feeder is a significant component of electrification network planning and design [Carter-Brown et al, 2005] and is considered the predominant sizing constraint [NRS 034, 2007] of distribution lines and equipment. Electricity providers are required to supply customers with a supply voltage that is allowed to fluctuate within a prescribed window dictated by QoS standards to ensure the appliances or equipment used by the residents work properly and are not damaged by an insufficient supply.

LV distribution systems of developing countries including those in Southern Africa mainly resemble the European method of LV distribution design which is characterized by long LV feeders as opposed to the North American method which employs shorter lines [Carr and McCall, 1992]. The consequence of using long lines is that it raises the significance of voltage drop along the feeders.

Various techniques and algorithms are used to calculate voltage drop at the design stage using the expected load, in its various forms, as an input parameter. The Herman-Beta method that incorporates probabilistic inputs and statistical calculation of voltage drop across LV feeders based on the Beta probability distribution function has been found to be the more superior approach [Sellick and Gaunt, 1995]. Usually the engineer has control over decisions such as which voltage calculation tool and load model to use to carry out calculations predicting the expected conditions on the feeders. Prescribing a system of analysis and design tools to be used by designers and planners reduces the sources of variation that might arise from the use of different analysis techniques. South Africa for example has set a standard that voltage drop predictions for all LV residential network designs be carried out using the Herman Beta algorithm, and a set of load parameters representing the maximum loads for different customer classes is provided [NRS 034-1, 2007]. This type of uniformity in design procedure allows for a more accurate identification of the short-comings of residential distribution system design, however, the prescribed tools must be accurate. Overall, for the different existing voltage drop estimation methods, the errors experienced in calculating voltage drop can be attributed to simplifications made in the calculations as well as "*uncertainty in the magnitudes and statistical properties of assumed loads, including uncertainty in load voltage dependency*" [Carter-Brown et al, 2005]

Quality of supply

National quality of supply standards are a key constraint in design activity. These standards are defined as the "*technical parameters to describe the electricity supplied to customers, and that used to determine the extent to which the needs of customers are met in the utilization of electricity*" [NRS 048-2, 2006]. The requirement for designs to comply with QoS standards was touched upon earlier in section 1.1. These standards ensure that customers do not suffer the consequences of poor quality of supply which might arise due to the cost saving actions of their power providers in designing and building the distribution network.

There are several quality of supply standards available that are in use worldwide which define the limits permitted for several parameters for a network to be deemed adequate. These parameters include frequency, dips, swells, interruptions, harmonics and voltage drop. However, in this research the voltage drop parameter is of particular interest as it is the constraint that has the highest impact on determining design parameters [Heunis and Herman, 2003; NRS 034, 2007]. QoS standards can have predetermined compatibility levels and limits within which the various parameters are required to be restricted. The compatibility levels define the range of values that the supply voltage is allowed to have in order for the devices connected to the network to operate efficiently. These ranges have been known to range between ±5% or ±10% in most standards [Kingham]. In cases where the supply voltage falls outside the compatibility levels, the Limit defined in QoS standards restricts the maximum deviation of the supply voltage.

Some standards such as South Africa's NRS 048-2 standard also include a time component to their specifications which brings about the significance of covariance between customers [Heunis and Herman, 2003]. This time component serves as an assessment period to evaluate the frequency of voltage parameters deviations outside set compatibility levels and limits on a network at the customer's end. It is thus strongly recommended that these compatibility levels and limits be taken into account in the development of design specifications, paying particular attention to the methods used to measure compliance of these restrictions [NRS 048-2, 2006].

1.4 MOTIVATION FOR THE RESEARCH

South Africa's NRS 034-1 [2007] document dealing with planning and design of distribution systems exposed a lack of connection between QoS standards and LV distribution planning and design standards stating, "*Electricity distribution networks are required to comply with the performance requirements of NRS 048-2 but there is currently no definitive link between this part of NRS 034 and NRS 048-2*". This lack of relationship between the two standards opens designers up to over or under-designing the networks. The QoS measurement methods defined in NRS 048-2 [2006] ought to be translated into design parameters that abide by the planning and design standards of NRS 034 [2007]. This will increase the likelihood that the networks built using the proposed design parameters will be less prone to QoS violations. However, the QoS standard must be dependable and clear in order to ensure that reliable design parameters are derived.

1.4.1 Probability distribution functions in load modelling

There has been much work done in planning and forecasting using the After Diverstiy Maximum Demand (ADMD) [Willis, 1996], however the use of average values as a representation of load maybe misleading as these figures do not take into account the stochastic nature of customer electricity demand. The use of probability distribution functions (pdfs) in load analysis has gained recognition throughout the years due to the ability of the pdfs to reflect this load attribute. The pdfs can be fit on load frequency distribution histograms. "Goodness of fit" were performed on various pdfs to assess how well they trend the load frequency histograms. Several pdfs performed satisfactorily in tests and have been utilized in prior and current LV network voltage drop analyses and designs. These include the Weibull, Beta, Gaussian and Erlang pdfs [ACE, 1981; Herman and Kritzinger, 1993; Davies and Paterson, 1962]. Herman and Kritzinger [1993] showed preference for the Beta pdf because of its ability to take on a variety of shapes as well as being restricted between 0 and 1 which are attributes that lend themselves well to representing residential load. Various methods of exploiting the beta parameters have been reported [Gaunt, 1999] but the application of the Beta pdf in load studies is not as prominent in literature and is somewhat confined to a specific group of researchers in South

Africa. The means of deriving statistical design parameters from basic ADMD information which is typically available in most countries is being studied [Herman and Gaunt, 2008]. If successful, this method will make probability models universally accessible.

1.4.2 Finding the appropriate parameters

The use of pdfs comes with many benefits. Firstly, efficient LV feeder voltage drop analysis algorithms such as the Herman-Beta algorithm currently used in South Africa can be developed. Also, probabilistic load models promise more precision than the traditionally used ADMD which does not sufficiently factor for the stochastic behaviour of load. Heunis and Herman [2003] compared models based on QoS standards and voltage regulation criteria. It was found that feeders designed based on voltage regulation standards were left exposed to QoS violations. The probability of exposure was prominent in shorter feeders with a small number of connected customers. These findings emphasize the need to merge QoS and voltage regulation criteria to formulate a single model which takes both constraints into account.

1.4.3 Contribution of research

The practice of cost mitigation is of worldwide significance especially in-light of the current state of the global economy. Taking into account the severity of connection costs discussed in section 1.1, the definition of relevant design parameters that allow LV network planners and designers to avoid unnecessary excess costs due to over-designing or under-designing distribution networks is essential. Incorporating QoS constraints into the design procedure will increase the probability of the LV networks operating within QoS limits, effectively mitigating the need to upgrade the network once it is built. This capital saving attribute will not only be of benefit to national utilities or independent energy providers but it will aid in advancing government aims such as the “electrification for all” strategies in countries such as South Africa [Bekker et al, 2008(b)], Kenya and Rwanda, or otherwise aid in the assessment of the validity of such policies.

1.5 HYPOTHESIS

Provisionally, this research will be specific to the South African situation and will then be generalized to a more global aspect. The problems and topics to be tackled in this research are:

- The purpose of NRS 034-1 is to guide the economic planning and design of residential LV networks capable of handling demand as well as complying with voltage limit regulations. The NRS 048-2 document on the other hand has specified the required compatibility levels and limits for voltage regulation as well as the methods and assessing compliance. The design criteria of the 2 documents have not yet been merged.

- When looking to generalize the derived parameters, making them usable in other countries, the voltage drop calculation techniques and the different QoS standards used in various countries and their methods of assessment should be considered. These differences might lead to a dissimilar set of results. The effects of these differences must be analysed so that the relevant effects can be accounted for by the derived parameters. The analysis part will also allow the assessment of the various QoS standards and suggestions of possible improvements for any short comings can be made.
- The derived parameters should be fairly simple so as to avoid misinterpretation. These parameters should also be able to be translated into the various input parameters used in the voltage drop calculation methods currently available.

The hypothesis is thus:

A process to select a set of simple parameters representing the load for the purposes of economic LV residential network planning and design can be derived that will allow quality of supply specifications to be satisfied

1.5.1 Research questions

The research questions that will enable the testing of the hypothesis are:

a) What are the available load modelling techniques and which method best represents the stochastic behaviour of residential load?
b) What are the available methods to calculating voltage drop at the design stage of an LV distribution network?
c) Have there been previous attempts to incorporate both QoS standards and voltage regulation into the design parameters and how successful were these ventures?
d) How do the risk levels associated with statistical methods of modelling and probabilistic voltage calculations factor into QoS compliance criteria? How do variables such as feeder dimensions and number found by Heunis and Herman [2003] factor into QoS violations.

1.6 REPORT FORMAT

The next chapter investigates the research questions posed in section 1.5.1 through an extensive literature review. Based on the finding in the literature, a methodology to derive the desired results is formulated and the results obtained are analysed. From the outcome of the analysis, recommendations are made and conclusions drawn.

2

LITERATURE REVIEW

Low voltage distribution systems are subject to technical, economic and supply quality constraints. For a design to be deemed feasible all three constraints must be taken into account and their standards must be met. Capital and operating costs constitute the economic factor. Curbing capital costs is usually the highest priority during electrification, but according to Willis [1997] the costs due to electrical losses over the system lifetime can become significant to the point of often surpassing the original capital costs of building up the network.

Voltage drop, short circuit current and equipment loading capacity make up the technical constraints. The short circuit capability can be calculated conventionally via deterministic procedure, whereas the voltage drop and thermal capacity require probabilistic description of the loads [Gaunt et al, 1999]. Voltage drop is a major factor when it comes to European style networks with significant LV feeders as it is a quality of supply indicator and is the main element used for the analysis of LV systems, particularly for extensive networks [Heunis and Herman, 2003].

Quality of Supply (QoS) criteria set the standards for the quality of the voltage supplied to the customers. The purpose of these criteria is to ensure customer equipment operates properly from the supplied electricity. The challenge is translating these QoS standards into implementable design parameters.

In this chapter literature encompassing the following subjects will be reviewed in order to answer the research questions posed in chapter one:

- voltage drop calculation methods,
- load modelling techniques,
- Quality of Supply standards, and

- previous attempts to include QoS standards into LV residential network design parameters.

There will also be a section describing the data capturing methods carried out during South Africa's Load research Project

2.1 METHODS OF CALCULATING THE VOLTAGE DROP OF AN LV NETWORK

This section draws freely from Sellick and Gaunt [1995] unless otherwise stated.

The North American and European methods are the most practiced in the field of LV distribution system planning and design [Carr and McCall, 1992]. The European method is characterized by [Herman and Gaunt, 2007]:

- 50 Hz supply,
- Longer LV feeders, and
- Transformer serving several customers

Whereas the North American method hosts the following features:

- 60 Hz supply,
- Shorter LV feeders (120/240V, laterals)
- Small transformers feeding a few customers

Voltage drop is a significant constraint when considering quality of supply, however, when considering conductor losses which are translated to cost, current is the dominant factor [Sellick, 1999]. This suggests that optimum conductor size can only be found by considering both voltage drop and current carrying/thermal capacity. However, in Southern Africa, as is the case which other developing countries, the European method is commonly practiced. The characteristic of long LV feeders increases the limitation imposed by voltage drop on conductor sizing, whereas for the short feeders the thermal capacity determines feeder size. This is due to the fact that voltage drop is a function of length [Sellick, 1999]. When describing grouped domestic loads, the voltage drop constraint is of more significance than the thermal capacity parameter [Herman and Kritzinger, 1993].

The reason for voltage drop calculations for reticulation networks is to predict the performance of the network in order to assess the adequacy of a pre-existing network and select cable routes and sizes when planning a network inter alia. If the voltage prediction technique does not satisfactorily represent actual performance, the design is vulnerable to over or under estimation

Figure 2.1 shows the basic model of a voltage calculation algorithm that takes into account the topology and loading which are specific to a network, to make design decisions.

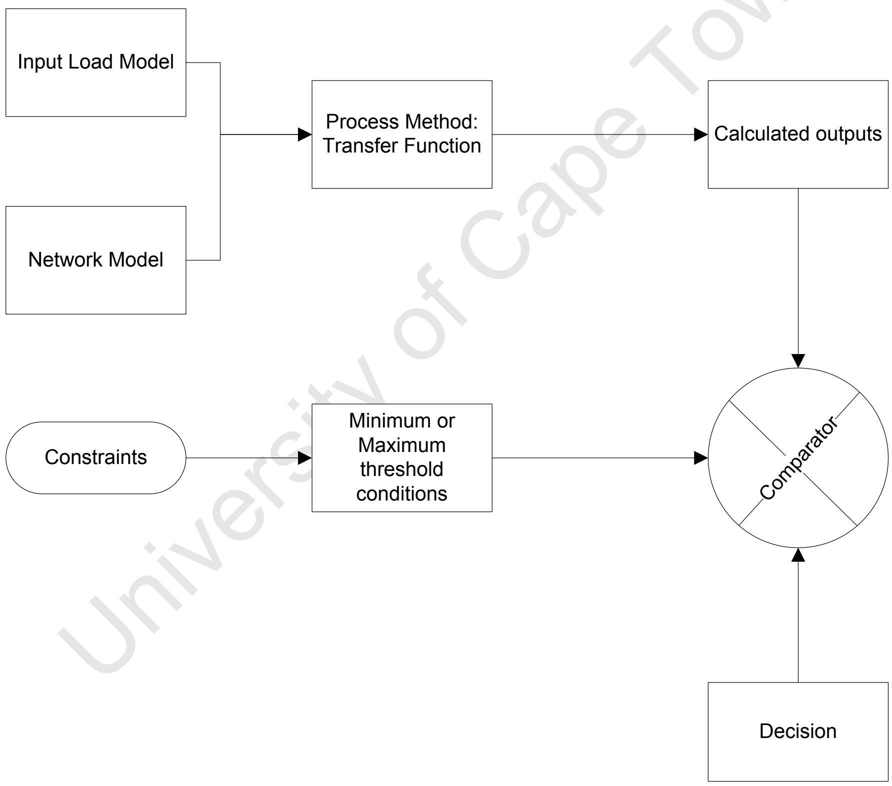


Figure 2.1: Flow chart of voltage drop calculation [Sellick and Gaunt, 1995].

The *Input Load Model* is an input parameter which represents customer loads at the time of maximum demand on the system and the consumers are usually assumed to be homogenous.

The *Network Model* is an input parameter which constitutes of customer allocation along the phases (if applicable), conductor resistance, network topology and source voltage.

The *Process Method* represents the network itself as a transfer function relating the associated currents, impedances and voltages to the *Network Model* parameters to calculate the voltage drop.

The *Calculated Outputs* may either be the predicted voltage or voltage drop whose value indicates the performance of the system being considered. These values are not to be confused as being the actual values but are rather an indication of the expected network performance.

The *Constraints* are the parameters the design is tested against to evaluate its' acceptability which can be several constraints associated to voltage drop, thermal rating of conductors and cost due to losses.

The *Threshold Conditions* are the limits that the *Calculated Outputs* of the design must be confined to in order to be deemed acceptable.

The *Decision* of whether the *Calculated Outputs* (Voltage drop, current rating or losses) are within an acceptable range is made by checking if the outputs fall within the *Threshold Conditions,* using a comparative approach.

2.1.1 Calculating outputs

The outputs can be calculated either deterministically or through Monte Carlo simulation. With the deterministic process, the *Transfer Function* produces a single valued output as an indication of network performance. The *Input Load Model* is also a singular value or parametric model of the load distribution e.g. the after diversity maximum demand (ADMD) which will be discussed later in the next section.

With Monte Carlo simulations the *Transfer Function* is applied to a range of randomly selected loads drawn from the *Input Load Model*. Therefore, a range of *Calculated Outputs* is expected whose range indicates the conditions that would be brought about from the expected loads. This technique involves multiple calculations using a variety of parametric load distribution models or real and typical distributions. Monte Carlo simulations take into account the stochastic quality of residential consumer loads and produce a range of voltage profiles based on the array of possible loading conditions e.g. the Gaussian distribution models which has 2 parameters μ(mean) and σ^2(variance).

Because of the array of results accumulated via Monte Carlo simulations, a risk value is used to select a single indicative value. The design risk is defined as "*the probability of exceeding the design percentile value*" and is independent of the community being designed for or load class [Heunis and Herman, 2003].The risk level selected to carry out a calculation translates into the uncertainty associated to the calculated value. For example a risk level of 5% (or conversely 95% confidence level), resulting in a certain calculated output value, means that there is 95% confidence the calculated value will not be surpassed. It does not mean that the feeder will experience the predicted voltage 5% of the time [ibid]. Low risk levels are conservative and usually result in high cost-low risk designs whereas high risk levels result in lower cost designs that are more prone to violating voltage drop conditions. The 10% risk level has commonly been used to calculate the voltage drop (no clear explanation has been found why 10% risk is used in the literature reviewed). Designers have the freedom to choose a risk level if they want to deviate from this 10% [NRS 034-1, 2007]. Heunis and Herman [2003] advise the designer to consider a) the percentage of time the feeder being designed will likely spend outside the design limit and b) the percentage of feeders that will never exceed the design voltage limit before selecting the risk level. The implication of varying risk levels needs to be empirically clarified.

The *Input Load Model* or design load is a projection of future loading conditions and represents the expected conditions on the network being designed. The design load, if not precise, may be an overestimate or underestimate of actual load. If it exceeds actual load, i.e. an overestimate, it is referred to as a conservative model which may result in the constraints not being violated but consequently leads to an unnecessarily expensive design.

The *Input Load Model* required to calculate voltage outputs depends on the type of *Transfer Function* being used. Accurate input models are required to calculate reliable outputs. It is recommended that the algorithm used to calculate the outputs be able to incorporate the topology of the network including branched sections. It is also recommended that the *Transfer Function* be sensitive to the supply voltage, *Input Load Model* parameters and the relationship between current, including current in the neutral phase, and impedance in order to be accurate. Assigning customers to different phases of the feeders and the number of customers at each node is defined by the designer and is important to voltage drop and loss calculations. Voltage drop calculations in particular are required to be sensitive to:

- the size and degree of stochastic imbalance of the loads (Load flow analysis methods are not applicable for voltage drop calculations for residential networks, due to the stochastic nature of residential load which require a statistical approach [Sellick, 1999]),
- the assignment of customers on the feeders as found in Herman et al [1998] (balancing the number of customers per phase or connecting customer to one phase at each node usually reduces the voltage drop), and
- the loss of diversity as the number of customers decreases along a feeder.

2.1.2 Voltage drop calculation methods

Several voltage drop calculation methods have been described in Sellick and Gaunt [1995]. These include:

1. <u>MONTE CARLO SIMULATION METHOD</u>

With this method voltage drops are calculated through simulation using a Beta pdf load model. This method takes into account:

- the neutral-to-line impedance ratio
- customer configurations
- supply voltage
- load model parameters and
- confidence level.

Monte Carlo simulations require large numbers of calculations which are time consuming in setting up each network and are therefore not deemed as appropriate for design operations.

2. BRITISH METHOD

The British method is an analytical algorithm that caters for unbalance and diversity through empirical formulae. It is quick to implement and can be used in spreadsheet format. This method however makes use of the following conditions:

- a neutral-to-line impedance ratio of 1
- empirical formulae based on a 10% risk level
- only the number of customer and not the arrangement of customers along the feeders is considered and
- the load distribution model is assumed to be Normal/Gaussian with an undefined standard deviation.

3. DT VDrop METHOD

This is a computer program that fuses the British method and a South African adaption of the British method called AMEU to calculate the expected drops from nominal voltage for customers connected to a network across all three phases. This method utilizes:

- empirical formulae based on 10% risk levels
- a single ADMD value and maximum current size
- a neutral-to-line impedance ratio

4. LOSS OF DIVERSITY METHOD

The loss of diversity method is derived from the Monte Carlo simulations method but it uses normally distributed input load models with varying slenderness factors ($s = \mu/\sigma$). This method provides a series of loss of diversity tables which require confidence level, slenderness factor and number of customers as inputs to derive output values.

Customer allocation is not considered and the neutral-to-line impedance ratio is assumed to be 1.

5. <u>UNBALANCE VOLTAGE METHOD</u>

This method takes a base case condition of consumers distributed evenly across 3 phases and modifies it by applying factors dependent on the number of connected customers. The derivation of this algorithm assumed loads are balanced on the feeder and its factors are derived from Monte Carlo simulations. Customer allocation is not taken into account however it caters for different connection philosophies. This method takes into account:

- the neutral-to-line impedance ratio and
- confidence levels.

6. <u>BETA DISTRIBUTION METHOD/THE HERMAN BETA METHOD</u>

This is a statistical method where the *Input Load Model* is a Beta pdf. The Beta method calculates the expected voltage drop by subtracting customer voltage to source voltage. Therefore this algorithm must be precise because customer voltage magnitude can be 20 times the voltage drop.

This method, unlike the rest accounts for:

- the neutral-to-line impedance ratio
- customer allocation
- input load model and
- confidence level

Comparative tests done by Sellick and Gaunt [1995] on all 6 techniques found the Herman Beta method to be the most reliable. The other methods were found to be prone to large errors especially when considering single phase networks.

All of the calculation methods are highly dependent on the accuracy of the *Input Load Model*. The *Network Model* is a representation of the design and can be highly accurate if the related conditions are incorporated into the calculation process. The problem is achieving a good representation of actual load through the *Input Load Model*. If this input parameter is not accurate it compromises the calculations process leading to results that are not indicative of the expected network performance. The input models must represent real life conditions in order to produce accurate estimates of likely conditions and are the focus of the following section.

2.2 LOAD MODELLING TECHNIQUES

Forecasting load magnitude and modelling the uncertainty of load are documented as the major sources of error when predicting the worst case load conditions to be used to produce accurate design parameters [Carter-Brown et al, 2005, Srinivasan et al, 1995, Alfares and Nazeeruddin, 2002, NRS 034-1, 2007]. Voltage drop calculations were found to be sensitive to errors in load magnitude predictions by Carter-Brown et al [2005] who support the continued efforts in improving load forecasting methods. Hobbs et al [1999] put a monetary equivalent on forecast accuracy, stating that as little as a 1% drop in the average short term forecast error would lead to savings of hundreds of thousands, or even millions of dollars.

With long term forecasting it is notoriously difficult to achieve accuracy and this is owed to a number of influential factors that **might** occur in this time period [Hamadi and Soliman, 2005]. With a networks lifespan ranging between 15 - 20 years the uncertainty lies in possible future developments, "*will the economy continue to expand so that the growth will develop as forecasted? Will a possible new factory (employment centre) develop as rumoured, causing a large and as of yet un-forecasted increment in growth? Will the bond election approve the bonds for a port facility (which would boost growth and increase load growth)*" [Willis, 1996]?

Willis [1996] defines accuracy as the ability of a forecast to ease decision making in the planning process and the level of precision should rather be judged on how effectively it carries this out instead of how closely it predicts future demand. In other words, in planning, the design is supposed to withstand the worst case scenarios which are likely to occur, not just withstand the normal typical day-day loads [Willis, 1996]. Willis' argument is that the model's requirement to cater for worst case scenarios leads it to be biased towards the circumstances leading to the worst case occurring, whereas accurate in the typical sense holds no bias to a particular event. Willis refers to this type of accuracy as representational accuracy, which is basically the ability of the forecast to predict load growth under conditions required for planning criteria and goals.

There have been numerous load forecasting techniques and a review of these can be found in Alfares and Naseeruddin [2002].

Accurately modelling design load is another major component in the design and operation of low voltage electricity distribution networks. Design loads have often been misunderstood [Herman and Gaunt, 2009]. In order to achieve accuracy, the stochastic and random nature of domestic load needs to be understood and addressed [Herman, 1989].

Along with the national load research project in South Africa, various independent researchers have recognized the following variables to have the most significant effect on load. These are, according to Heunis et al, 2000:

- Household income
- Stated time with electricity which may not necessarily coincide with the time since electrification,
- Hot Water Cylinder (HWC) penetration
- Floor area

Income has been identified as the most significant demographic parameter influencing maximum demand of a customer [Herman and Gaunt, 2005]. This observation is logical as the amount of disposable income available to a household contributes to appliance penetration by enabling residents to purchase electrical appliances and pay for the energy consumed.

The power required to operate the different appliances makes up the load magnitude. Hot water cylinders (HWCs) or geysers are major contributors to a household's load profile because of their high power demand. HWCs are so significant that consumers are sometimes broadly classified into 2 groups which are those with or without HWCs [NRS 034-1, 2007]. Demand side management (DSM) activities involving HWC control can drastically affect load. HWC-DSM efforts were found by Herman and Gaunt [2009] to alter previously established characteristic load parameters for South African consumer classes and subsequently alter voltage conditions, see table 2.1. HWC-DSM basically involves automatically switching off HWCs during peak hours after which the cylinders are switched back on. If the cylinders are switched back on simultaneously it results in a cold-load pick-up condition that increases the demand load current for the customer and within the network. From their simulations, Herman and Gaunt [2009] found that on average the cold-load pick-up ADMD would be 30% higher than the ADMD at community peak time.

Table 2.1: Results for analysis for HWC-DSM where peak demand occurs between 18:00 and 20:00 [Herman and Gaunt, 2009]

	Mean	STD	+1 STD	Alpha	Beta	CB	V-Drop (%)
Cold Load Pickup at 20:00	15.669	9.673	25.342	1.914	7.86	80	6.68
Load at 18:00 (No DSM)	10.551	9.089	19.640	1.038	6.83	80	5.04
Load at 20:00 (No DSM)	10.066	8.618	18.684	1.067	7.41	80	4.80
Maximum Demand(No DSM)	12.524	10.190	22.714	1.118	6.02	80	5.86

Heating and cooling appliances have also been found to contribute significantly to the level of demand, based on their level of energy consumption.

However, In light of all these factors, community habits or customer behaviour have a major impact on the unpredictable behaviour of the load. The variability of electricity use generally depends on the presence of occupants and the time of use of the high power appliances [Carpento and Chicco, 2008]. That is, it is usually necessary for consumers to be present in the house for electricity to be consumed [Bladh and Krantz, 2008]. Wright and Firth [2007] identify occupancy as a contributor to domestic load patterns. The worst-case state of a LV network that is designed for has typically been defined as the most heavily loaded conditions [Herman, 1989] which have also been assumed to result in the worst voltage conditions along the feeders. But because of the diversity trait in residential load, networks do not necessarily have to cope with the worst possible load combinations as they may not lead to the worst case voltage conditions [Dickert and Schegner]. It is therefore important that a load model be sensitive to the magnitude diversity and stochastic behaviour of residential load.

In this section, 3 types of load modelling techniques will be discussed. These are the deterministic, bottom-up and statistical methods. The discussion will include a description of the models and detail the pros and cons of each approach.

2.2.1 Deterministic load modelling

With the worst case traditionally assumed to be maximum demand, deterministic procedure involves predicting the coincident ADMD usually in kVAs (Kilovolt Amperes). The ADMD is maximum average load for a group of consumers each drawing a load corresponding to the appliances in use [Heunis and Herman, 2003]. There has been abundant recorded research into finding the representative ADMD [Willis, 1996] and it is prevalent engineering practice for maximum demand estimation in LV networks to be based on the After Diversity Maximum Demand [McQueen et al, 2004]. For an infinite sample the ADMD is defined as the average load per customer at a particular time and duration. Taking the sample size to be N, the maximum demand for the sample in this case can correctly be defined as N times the ADMD. The effect of diversity increases with a decreasing number of customers [Dickert and Schegner,] and the relationship between maximum demand and ADMD is no longer simply N times the ADMD [NRS 034-1, 2007].

The basis of diversity is that customers can experience load peaks at different times. Traditionally this diversity is accounted for using a coincidence factor. The coincidence factor is defined by Bary [1945] as the ratio of the maximum coincident total power demand of a group of consumers to the sum of the maximum power demands of the individual consumers comprising the group, both taken at the same point of supply and for the same period of time. Dickert and Schegner define it as "*the coincident peak demand of a group of customers within a specified period to the sum of their individual maximum demands within the same period and can be between 0 and 1*." Therefore the maximum diversified demand for a group of N customers is obtained by applying the coincidence factor to the product of the maximum average demand and N, given the coincidence factor shares a similar demand interval, time period and load units as the maximum demand [Nickel and Braunstein, 1981]. Each customer set drawing a particular set of individual maximum demands and total maximum demand has a specific coincidence factor. Rusck [1956] found the coincident factor to be:

$$\mathrm{CF} = c\infty + (1 - c\infty)(n^{-\frac{1}{2}}) \qquad \text{...Equation 2.1}$$

where:

c∞ is the ratio the mean load and the maximum demand per customer and

n is the number of customers.

For this method it was assumed that the demand at the time of maximum demand was normally distributed and that either all customers draw the same maximum demand or an average maximum demand per customers was applicable.

Nickel and Braunstein [1981] reported the equation 2.2 to be the formula for the coincidence factor based on measured load data in the United States where homogeneity in demand levels was also assumed.

$$\mathrm{CF} = 0.5 \times (1 + \frac{5}{2n+3}) \qquad \text{...Equation 2.2}$$

where:

n is the number of customers

An alternative to the coincidence factor is the diversity factor, a reciprocal of the coincidence factor. This is defined by the AIEE as the "*ratio of the sum of the maximum power demands of the subdivision of the system or part of the system to the maximum demand of the whole system or part of the system under consideration at the point of supply*" [Bary, 1945]. The diversity factor can be equal to or larger than 1 [Dickert and Schegner].

It is impractical to apply the coincidence factor to a non-homogeneous load class based on the assumptions of equal individual maximum loads and like load cycles used to derive the coincidence factors [Nickel and Braunstein, 1981]. And, with newer design standards requiring a more in-depth understanding of the nature of demand this approach is left wanting. A singular value omits information such as duration and probability [Dickert and Schegner]. Uncertainty is best dealt with a probabilistic technique [NRS 034-1, 2007] as the correction factors are said to become more uncertain when dealing with a small number or customers connected to a feeder (<15) as is common in rural communities [Ferguson and Gaunt, 2003, Nickel and Braunsteien, 1981].

2.2.2 Bottom-up models

Bottom-up modelling methods are used to model time dependent residential loads. These models are typically in the form of load profiles which are defined as graphical representations of trends in appliance use where periods with similar trends are grouped together to form typical load profiles [Heunis and Herman, 2003]. The bottom-up models thus give more detailed information on residential customer behaviour [Dickert and Schegner]. The bottom-up method, or alternately the end-use approach, gives detailed information on the subsets or elements making up the residential sector. Bottom-up models can be used to distinguish electricity at three category levels below the system level [Willis, 1996]. These levels are:

- customer classes level,
- end use classes level (i.e. cooking, cleaning, entertainment ...) within each customer class and
- appliance level categories within each end use.

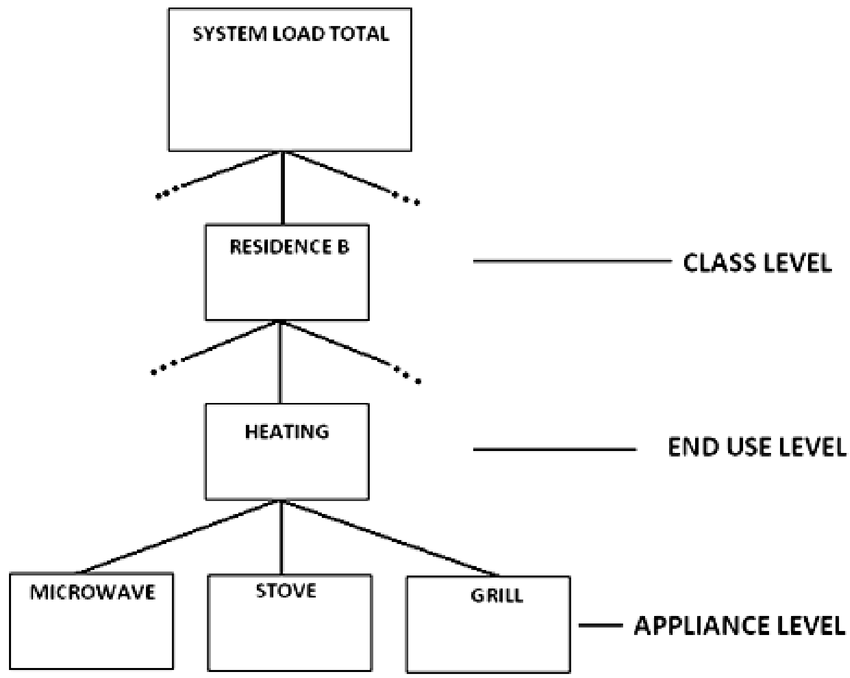


Figure 2.2: Basic construct of End Use (bottom up) models [Willis, 1996]

Load profiles at the different levels can be generated by aggregating load profiles from lower the levels, with appliance level being the most elementary. Figure 2.3 shows a possible mode of generating load profiles for a household using a bottom-up modelling technique. The input data constitutes behavioural, class and appliance information. From this information load patterns for each appliance is generated and summed to produce the household load curve. Similarly the load profiles at the different levels in figure 2.2 can be produced by summation of the lower level profiles.

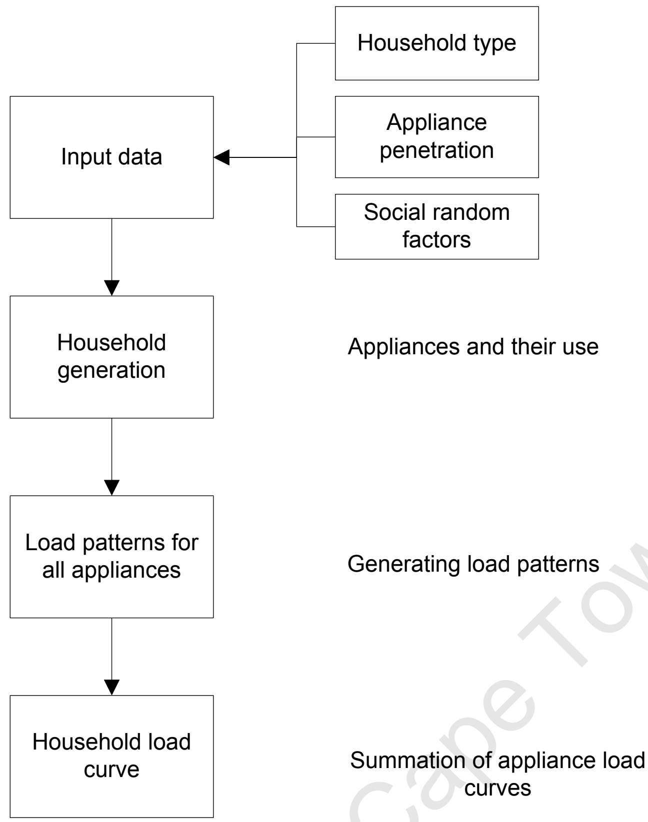


Figure 2.3: Diagram showing a possible bottom-up load profile generation [Dickert and Schegner]

Walker and Pokoski [1985], who were one of the first to incorporate customer behaviour into a bottom-up household load model, utilized two behavioural functions to build up the profiles. These functions are:

- Availability - A statistical estimate of the number or people in a household available to use an appliance and
- Proclivity - The probability that the occupant will use that specific appliance at a given time of day.

Walker and Pokoski [1985] reported that the model was bound by the fact that customer availability and proclivity are directly or indirectly functions of variables such as price of electricity, job locations, social trends etc. Despite this limitation, after aggregating the appliance models to compile a full load model of the household, the simulated approach itself compared to actual load data indicated that the approach was viable.

Using data from Italian households, Capasso et al [1994] took the behavioural functions further and included:

- Availability of each member of the household,
- Electrical activities categorized as housework, personal hygiene, cooking and leisure,
- Appliance usage
- Human resources i.e. eyes, ears, hands etc. This was to ensure activities such as using a hairdryer and flat iron could not be used at the same time by one occupant. (From personal experience, while rushing to catch lectures I should say it is very possible to use a hairdryer and flat iron at the same time. You cannot use them simultaneously but you can definitely have them on at the same time. And did I mention I am usually boiling an egg for breakfast while doing all of this?)

Capasso et al also included engineering probability functions on top of the behavioural functions which included:

- Mode of operation of appliance i.e. cycle or activation time, power demand, and average annual consumption,
- Household demand limit,
- Technological penetration i.e. the saturation of appliances representing any technological innovation.

The model was reported to be very promising but was in need of further development in terms of weather dependent aspects, the affects of different tariff structures etc.

In their work, Richardson et al [2008] define an active occupant as a person who is awake in the house. Their model introduced a different factor that influences appliance use and that is sharing appliances e.g. devices for lighting, heating and cooling. The sharing of appliances assumes that doubling the number of occupants in a household is unlikely to double demand in all instances for example, when you consider lighting demand.

Appliances can be grouped into different categories depending on method of use.For example [Dickert and Schegner]:

- Appliance use independent of the customers' presence e.g. refrigerator
- Appliance use dependent on the consumer but not the day of the week e.g. washing machines, and
- Usage dependent on the customer and weekday e.g. Television

Richardson et al (2010) modelled the varying likelihood of usage of each appliance through stochastic simulations. This involved using an "active occupancy" model, related to the number of people at home and awake, as well as the occupants' "activities" such as cooking etc, to develop "activity profiles" for each appliance. While Richardson et al [2010] used static activity profiles, Widen and Wackelgard [2010] constructed Markov-chain based occupant activity simulations, mapping each activity to an appliance group end-use to develop their bottom-up model.

Bottom-up models are reputably accurate as they take into account both load magnitude and stochasticity, as the use of appliances for lighting, space heating and water heating in a household varies significantly with respect to time, mainly in accordance with the activity of the buildings occupants [Richardson et al, 2008]. Taking occupancy patterns into account improves the modelling of diversity [Stokes et al, 2004].

Yao and Steemer [2005] say that in order to predict the domestic load profile it is essential to identify the pattern of electricity use which is related to the occupancy period and go on to state that the load profile is very much dependent on the occupancy pattern. Occupant behaviour will tend to follow a more regular day-to-day patterns since habits such as the time people get up or go to bed are fairly consistent each day [Stokes et al, 2004]. Also for samples with more than 30 customers a trend in usage will appear [Heunis and Herman, 2003]. For small sample sizes of less than 10 - 20 customers, load variations are typically significantly high and are highly dependent on the number, type and lifestyle of consumers [Carpento and Chicco, 2008] which are aspects best handled by the bottom-up approach.

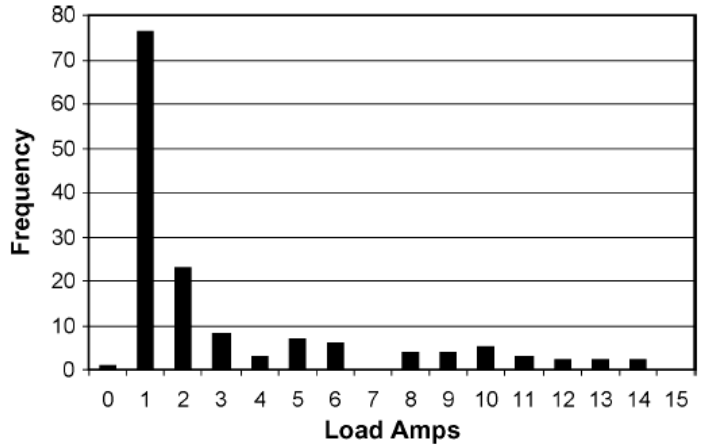
The data available to most electric utilities on domestic electricity consumption does not typically include detailed information on the end-use activities in individual households [Paatero and Lund, 2006] and recording behavioural data e.g. time of use data, occupancy times etc in different households is generally expensive, time consuming and highly dependent on participants diligently reporting all their activities for a sufficient period of time. These models may not be suitable to handle pre-electrification circumstances as they require information about consumers and their habits which is not usually available prior to electrification [Heunis et al, 2000].

2.2.3 Probabilistic load modelling

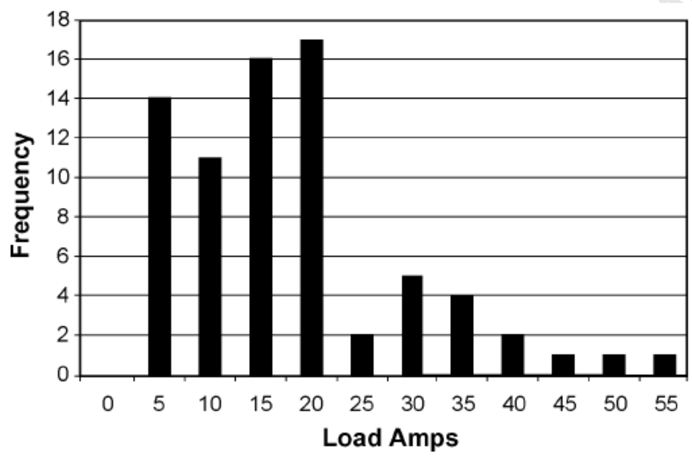
A statistical model in essence finds the relationship between 2 or more variables that are stochastically related.

Having analysed a significant amount of data collected in South Africa, it was found that domestic electric loads can be modelled as constant current sinks [NRS 034-1, 2007]. The heaviest loads, which contribute significantly to the overall load magnitude, have a large resistive heating component that results in a close to unity power factor. This has led to the adoption of loads being modelled as currents at unity power factor to calculate voltage drop [ibid]. These adjustments simplify the calculation of voltage drop.However, Heunis and Herman [2002] warn that constant current models may lead to over estimates of voltage regulation and losses when dealing with very low income consumers.

Frequency histograms may be used to summarize the behaviour of one consumer's load over a period of time by showing the dispersion of load currents. Similarly they can be used to display the average loads for a group of customers over the same period of time (refer to figures 2.4 (a) and (b)). The shape of the histogram may be able to conform to one or more of the known pdfs.



(a)



(b)

Figure 2.4: Typical histogram of the load current distribution for (a) low income and (b) middle income group at the time of the groups' maximum demand [Herman and Gaunt, 2008]

Traits and assumptions that commonly represent residential load are:

- Residential load does not include generators thus the load is never negative. Therefore, the minimum load that can be drawn is 0A
- It is finite and can be bound to a certain maximum current using load limiting circuit breakers

- Load histograms show levels of skewing in the form of histograms as found from the data collected in South Africa. The extent of the skewing corresponds to various socio-demographic factors.

Hamilton [1944], Rusck [1956] and Davies and Paterson [1962] had all assumed that the loads were normally distributed at the time of maximum demand. However, in 1991 it was reported that the Gaussian did not satisfactorily represent the loading and voltage drop along the feeder [Gaunt et al, 1999]. This was mainly because unlike the traits of residential load previously listed, the Gaussian pdf cannot skew, it has infinite boundaries and it can exhibit negative values. The skewing of the load function holds significance in that it "*affects the estimation of upper bound confidence limit of the diversified maximum demand*" [Herman and Gaunt, 1991] and depends on socio-demographic factors as well as factors such as the use of hot water cylinders and circuit breaker size (figure 2.5).

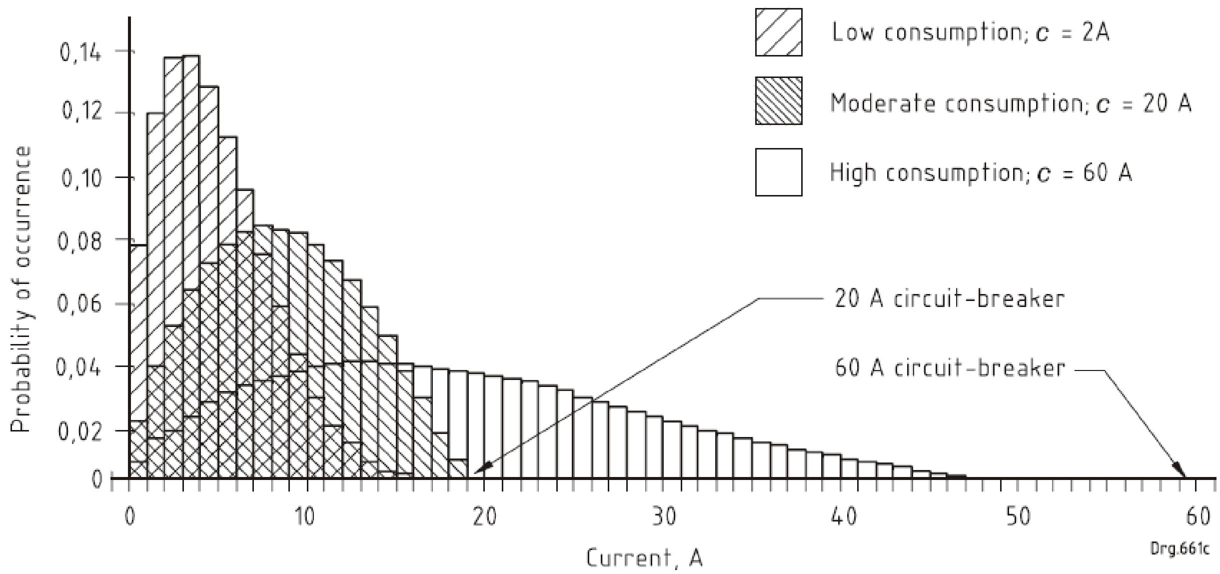


Figure 2.5: Typical load distributions [NRS 034-1, 2007]

Despite these findings the use of the Gaussian (Normal) pdf has not been disregarded. It is favoured for its simplicity and there are a number of analysis tools that have been well developed, based on Gaussian pdf, that are reported in literature. The Gaussian probability function is easy to incorporate into many computational tools e.g. state estimation functions, unlike the other parameter distributions [Singh et al, 2010]. The use of the Gaussian pdf is also appropriate when dealing with combined loads of sample sizes greater than 30 [NRS 034-1, 2007]. This is because for a greater number of households, data will converge towards the mean in accordance with the Central Limit laws [Willis, 1996]. This Central Limit Law, otherwise known as Central Limit Theorem, states that "*given a distribution with a mean* μ *and variance* σ^2*, the sampling distribution of the mean approaches a normal distribution with a mean (*μ*) and a variance* σ^2/N *as N, the sample size, increases*." The transition to a normal distribution is independent to the original shape of the distribution [Lane]. The effects of Central Limit Theorem can be found in the work of Paatero and Lund [2006]. Whilst developing a load forecast model using Finnish data, Paatero and Lund observed that the distribution of the daily electricity consumption of 702 households,about the mean, after compensating for factors such as weather, was normally distributed. 702 is a number well within the range of influence of the central limit and is most likely the reason behind the Gaussian trend. The number of customers connected on a feeder can often be below 30 and the uncertainty of the load increases for a decreasing sample size. Thus, the load may exceed N times the mean value, where N is the number of customers connected to the feeder [NRS 034-1, 2007].

An interesting way to handle the Gaussians inability to skew is reported in [Singh et al, 2010]. Singh et al developed a Gaussian Mixture Model (GMM) which essentially involved combining several normal distributions of varying means and variances to create different types of load distributions (figure 2.6). This is in light of having observed that the pdfs at different buses were unlike (figure 2.7).

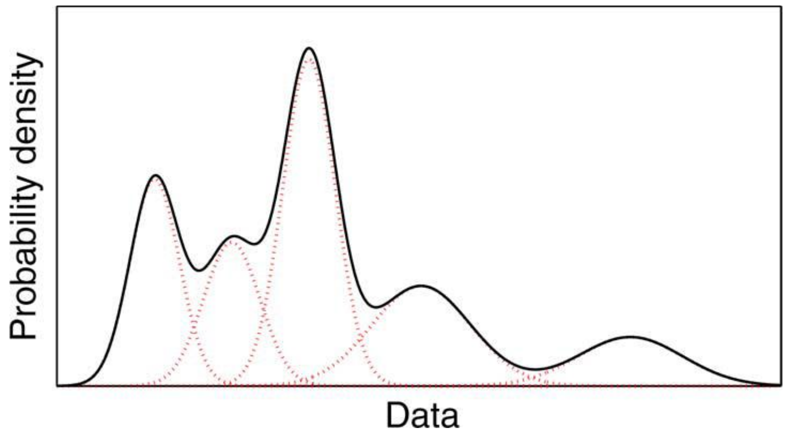


Figure 2.6: Gaussian mixture approximation of density: Dotted lines represent individual mixture components and solid line represents the resultant density [Singh et al, 2010]

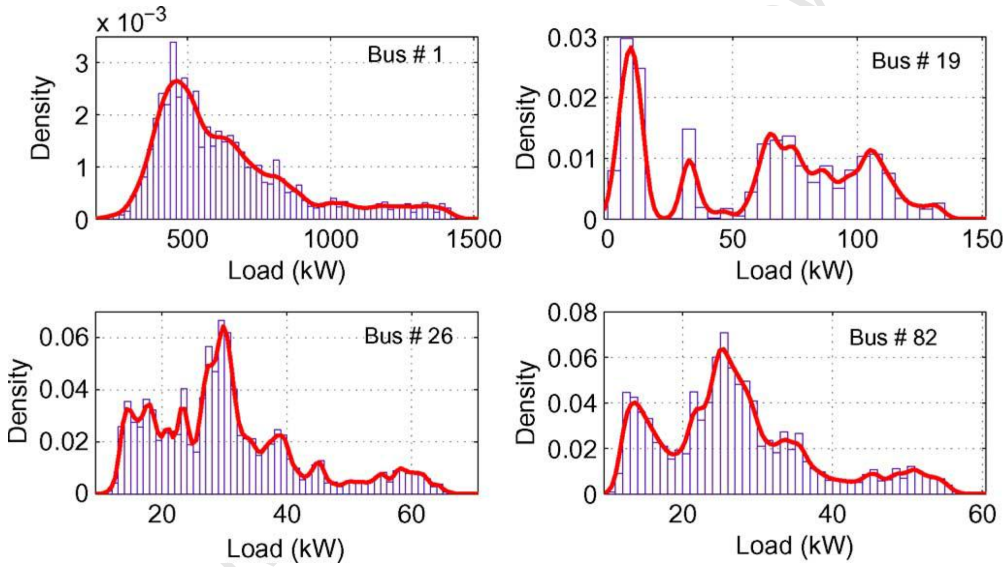


Figure 2.7: Probability distribution of load at different buses [Singh et al, 2010].

After performing the Chi-Square goodness of fit test on load histograms for the loads for bus 1 and bus 19 shown in figure 2.7, using the GMM, Normal, Log-normal, Beta and Gamma distributions, the GMM performed the best in both cases.

Alternately, Seppala [1995] using Finnish data suggested using the Log-normal distribution to model load. Also, having carried out numerous Goodness of Fit tests using the Kolmogorov-Smirnov test (KS) for the Beta, Gamma, Gumbel, Log-normal, Rayleigh and Weibull, Carpento and Chicco [2008] found the Gamma, Log-normal and Normal probability distributions to be the most suitable. Log-normal and gamma distributions are confined to a positive domain and can skew to the left unlike the Gaussian and more similar to load. The Log-normal and Gamma distributions are strong fits for histograms with tails in the directions of the variable's maximum but the functions cannot handle histogram tails in either direction of the variable's maximum or minimum. The function that can accommodate these variations in skewing is the Beta pdf [Cross et al, 2006].

Attributes of the Beta pdf include:

- A lower limit of 0 and a upper limit of 1 therefore values can be scaled to fit between its upper and lower limit of 0 and 1
- It is able to skew to the left (a trait typical for customers with unrestricted electricity use) and take on a bathtub or right-skewed shape (typical for loads of consumers restricted by 2.5A and 10A circuit breakers) [Heunis and Herman, 2002].
- Its' parameters can be easily generated from the mean and standard deviation of the data as each customers' load currents have a mean and standard deviation (or variance) [Heunis and Herman, 2003].

The Beta pdf does not always outperform the other pdfs in all possible cases of skewing, particularly when skewing to the left as can be seen in Seppala [1995], Carpento and Chicco [2008] and Singh et al [2010]. The Beta pdf however has the best overall performance in the 'goodness of fit' tests. Herman and Kritzinger [1993], having carried out Chi-Square and Kolmogorov-Smirnov (KS) goodness of fit tests on South African data using the Weibull, Gaussian, Erlang and Beta pdfs, found the Beta distribution to be the best suited probabilistic representation of residential load. An independent study by Ghosh et al [1997] where a Chi-Square goodness-of-fit test using the Normal, Log-normal and beta distributions was applied to loads showing different levels of skewing, the Beta pdf was found to be the overall strongest function. Preference for this function is based on its ability to take on a variety of shapes that can represent the different forms a load histogram can take. Figure 2.8 illustrates the Beta pdfs versatility.

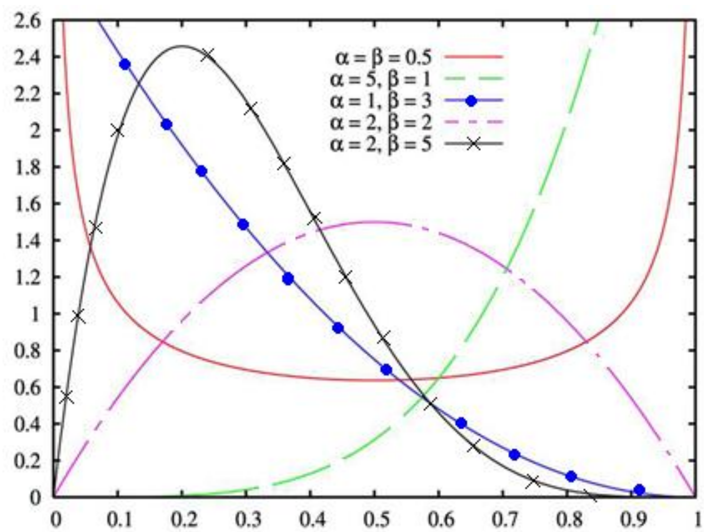


Figure 2.8: Beta pdf for different values of α and β [Cross et al, 2006]

In South Africa work has and is being done to develop load models based on the Beta pdf such as the work by Heunis and Herman [2002] and Herman and Heunis [2003] that can cope with mixed loads, fixed loads and constant power loads. So far the models developed have been successful, especially when dealing with samples of more than 10 customers, as the error in estimation is reduced to levels deemed acceptable for practical purposes [Heunis and Herman, 2002]. McQueen et al [2004] warn that statistical methods based on the Beta function become difficult when dealing with branched networks with a large number of connected customers.

2.2.4 Applications of the Beta pdf

It was mentioned in section 2.2.3 that the Gaussian function is popular because it is simple, easy to manipulate and has numerous analysis processes that are custom made for it. However, three major analysis tools have been developed around the Beta pdf. These are:

- The Herman-Beta method for voltage drop calculations
- The Beta parameter plot
- Coefficient of Variation (COV) curve

<u>THE HERMAN BETA METHOD</u>

The Herman-Beta method is a statistical method of calculating voltage drop expected across a feeder system that has been discussed in section 2.1. It has been found through rigorous testing using Monte Carlo simulation techniques to be superior to the other voltage analysis tools for LV residential network design [Sellick and Gaunt, 1995, Herman et al, 1998] and is prescribed in South Africa as part of the National design guidelines [NRS 034-1, 2007].

With the Herman-Beta method:

- different values of α,β and c can be specified at each node and it allows for a mixture of load classes along the feeder,
- α,β and c parameters can be derived for a mixed load class and fixed loads and be input into the algorithm for voltage drop calculations [Herman and Heunis, 2003]

The difficulty of using the Herman-Beta method is in selecting the representative α, β and c for the community being designed for. Ferguson and Gaunt [2003] demonstrated this dilemma by showing that different communities can have the same ADMD but have different α, β values because of the socio-demographics factors of the community which the ADMD does not take into account.

<u>THE BETA PARAMETER PLOT (BPP)</u>

The traditional Beta pdf is governed by two parameters α and β where:

$$\alpha = \frac{\mu(C\mu-\mu^2-\sigma^2)}{C\sigma^2} \qquad \text{...Equation 2.3}$$

$$\beta = \frac{(C-\mu)(C\mu-\mu^2-\sigma^2)}{C\sigma^2} \qquad \text{...Equation 2.4}$$

Where:

μ = mean of the load (or ADMD)

σ^2 = variance of the load

C = scaling factor

The Beta parameter plot was developed by Gaunt [1999] by rearranging equations 2.3 and 2.4 to get a relationship between α and the independent variable μ/C (normalized mean). The result was a plot that displayed the load current distribution at a certain time as a single point rather than a continuous distribution as in the case of the regular Beta pdf.

An example of a BPP plot is given in figure 2.9 which shows a plot for a middle income South African community Helderberg using 5 minute averaged load data collected between July and December in 1997.

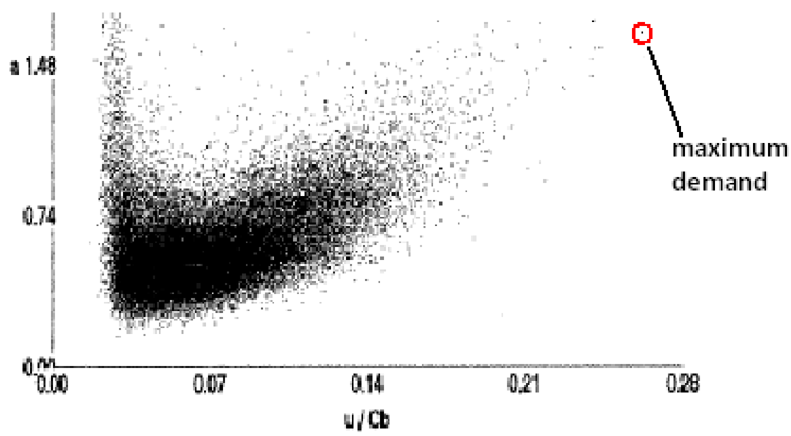


Figure 2.9: Helderberg 1997 (July - December) [Gaunt, 1999]

The overall shape of the BPP is subject to factors such as current limiting, appliance types and homogeneity of social behaviour or the customers. Upon inspection, an error in equation used to derive the BPP by Gaunt [1999] was found during this study. The corrected derivation is given in chapter 3.

<u>THE COEFFICIENT OF VARIATION (COV) CURVE</u>

With the ADMD being the simplest modelling method and used in most countries Herman and Gaunt [2008] identified a relationship between the ADMD and the coefficient of variation, shown in figure 2.10. This opens up the use of pdfs to countries without a substantial database of real load data to produce accurate and representative probability functions.

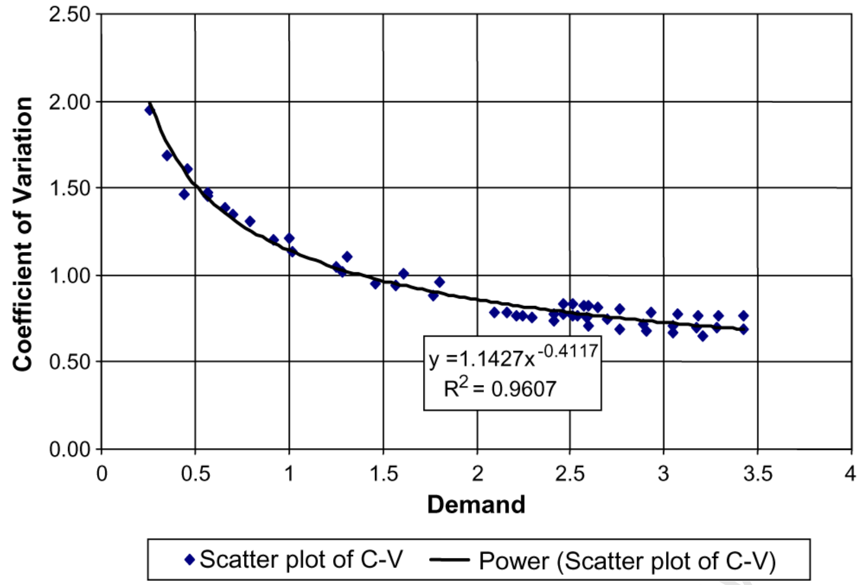


Figure 2.10: Coefficient of Variation VS ADMD (kVA) [Herman and Gaunt, 2008]

This relationship termed the COV (coefficient of Variation) curve was based on the load parameters (Appendix A, figure A2) of domestic customers used in South Africa. The COV curve was found to be independent of customer class. The relationship, with a high correlation factor of 0.9607 to the load parameters, was found to be:

$$\gamma = 1.1427 d^{-0.412} \qquad \text{...Equation 2.3}$$

where:

γ is the coefficient of variation

d is the demand in kVA

2.3 QUALITY OF SUPPLY STANDARDS

This section draws freely from [NRS 048-2, 2006] unless otherwise stated.

Quality of supply is defined as “*technical parameters to describe the electricity supplied to customers, and that are used to determine the extent to which the needs of customers are met in the utilization of electricity*” [NRS 048-2, 2008]. These technical parameters include power frequency, variations in supply voltage, voltage dips, short and long term interruptions, harmonics etc. Quality of supply standards provide planners with minimum standards and criteria to plan and design distribution networks and provides a means of evaluating the performance of the network based on the criteria of the standard. There are numerous QoS standards in use worldwide including EN 50160 (Europe), NVE (Norway), NRS 048-2 (South Africa, Namibia), ANSI C84.1 (North America). NRS 048 - 2 states that the standards should apply under normal operating conditions which exclude situations such as temporary supplies during times of maintenance or equipment failure and unavoidable circumstances such as theft and damage through extreme atmospheric phenomena, malice, accidents and unavoidable circumstances, war etc. Normal operating conditions constitute the conditions within which the network is assumed to operate under and is designed for.

Kingham while examining the European standard EN 50160 brings up three issues common to most power quality standards. These are;

1. The Standards are consensus driven, typically representing the lowest agreed upon value for power quality limits,
2. Measurement techniques are inadequately defined. Kingham states that "*by allowing utilities to evaluate compliance with undefined measurement methods, it will be impossible to compare results or apply fair non-compliance penalties*."
3. Some characteristics are not evaluated for the full measurement interval, or a certain percentage of measurements are disregarded. This essentially means that for that disregarded time there are no limits on the degree of supply voltage variations. E.g. EN 50160 allows 95% of the 1 week evaluation period to be monitored [Markiewicz and Klajn, 2004, Klajn 2008], whereas NRS 048 requires 100% monitoring for a minimum of the same period.

China and South Africa are reported to be the countries with more clearly defined measurement methods of QoS compliance in their associated quality standards [Kingham]. South Africa has seen 3 editions of its NRS 048-2 power quality standards. The changes in the standards were reported to be motivated by similar reasons to that raised by Kingham [Koch et al, 2007]. The 3rd edition of NRS 048 specifies;

- limit levels
- compliance levels and
- assessment methods

2.3.1 Compatibility Levels

Definition: "*Specified disturbance level at which an acceptable, high probability of electromagnetic compatibility should exist*" [IEV 161-03010/A, as cited by NRS 048-2, 2006].

Selection of probability levels is based on the high probability of equipment being supplied operating correctly and also a high probability for the network to operate within the required limit. Therefore, the South African standard also describes the compatibility level as "*the level of disturbance for which, with a suitable margin, equipment operating in the relevant environment is required to have immunity*." The compatibility level is related to the statistics of the QoS parameters that, at any given time, show a spread of probabilities. This spread depends on variables such as load, climate and geographic location. The concept of compatibility levels is illustrated in figure 2.11 for a parameter showing a normal distribution. A planning level is the "*level to which a utility designs its network when it evaluates the impact on the supply system of all loads connected to the system*" [NRS 048 – 2, 2006].

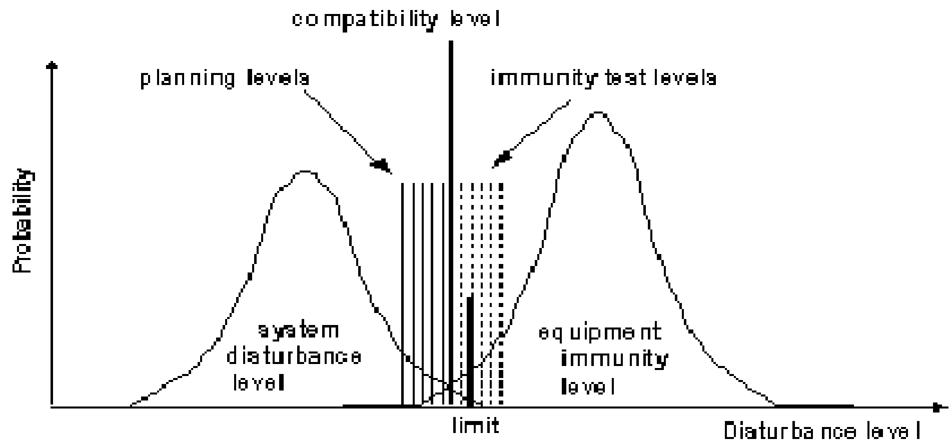


Figure 2.11: Illustration of concept of compatibility levels [NRS 048-2, 2006]

The principle of NRS 048-2 is to set compatibility levels so that 95% of the probability levels for the upper limit of system disturbance levels are represented. Voltage magnitude has an upper and lower compliance level and can exhibit pdfs that are not Gaussian. Standard or declared voltages in South Africa are typically √3*230V phase-to-phase or 230V phase to neutral. Compatibility levels for supply voltage are given in table 2.2.

Table 2.2: Deviations from standard or declared voltages [NRS 048-2, 2006]

Voltage Level (V)	Compatibility Level (%)
<500	± 10%
>= 500	± 5%

An extra constraint on supply voltage magnitude is stipulated by NRS 048-2 which is that 2 or more consecutive 10 minute periods are not allowed to be in violation of compatibility levels. This criterion was added to avoid violation occurring over long periods of time possibly exceeding equipment design points.

2.3.2 Limit Levels

Because of the stochastic nature of power quality parameters and load, insuring 100% compliance is next to impossible. The purpose of limits is to address the maximum magnitudes permitted for a QoS parameter. That is to say, if a parameter goes above a compliance level and is deemed a violation, the magnitude it is allowed to reach is defined by the limit level. Basically, "*limits are specifically introduced to ensure that extreme exceedance of equipment design standards is avoided*" [NRS 048-2, 2006]. Limit levels can also be violated in situations where compliance is not tested for the full inspection period which was one of the concerns brought out by Kingham.

Limits for supply voltage are given in table 2.3.

Table 2.3: deviations from standard or declared voltages [NRS 048-2, 2006]

Voltage Level (V)	Limit (%)
<500	± 15%
>= 500	± 10%

2.3.3 Assessment Methods

NRS 048-2 [2006] has a standard assessment period of a minimum of 1 week constituting 7 consecutive days starting at 00:00 on the first day to 00:00 after the last day. For long periods such as 2 weeks a weekly value is attained through a daily sliding method. For example, a two week period will result in eight periods of 1 week each. The duration was adopted from the EN 50160 standard. There is no specification for when in the year the assessment period should be selected.

The assessment level is defined as the "*level used to evaluate the measured values at a particular site against compatibility levels*." The highest and lowest measured 10 minute r.m.s (root mean square) values for supply voltage that are not exceeded 95% of the time are compared with the compatibility levels. In other words up to 95% of measured 10 minute values are required to be compliant or alternately 5% are allowed to be in violation of compatibility limits.

The averaging times vary between standards. For example, NRS 048-2 uses data averaged over 10 minutes and the Polish power quality standard requires 15 minutes [Markiewicz and Klajn, 2004]. Comparing with data averaged over a 2 minute period, Herman and Kritzinger [1993] found averaging over a 5 minute period to be optimal as it only reduced the ADMD recorded with 2 minute data by an average of 0.9% and it met the Nyquist criterion for the 10 minute period specified in South Africa. Averaging over a 10 minute period was found to reduce the 2 minute ADMD by 3.1%. Gaunt et al [1999] also carried out experiments on the effects of the averaging period. It was found that periods shorter than 5 minutes mainly contributed to the accumulation of large amounts of data but had negligible effects on recorded current values. In the context of voltage drop calculation Sellick [1995, as cited by Sellick, 1999] found that changing the averaging period from 1 minute to 5 had no significant impact on the calculated output.

2.4 VOLTAGE REGULATION AND QUALITY OF SUPPLY

Voltage regulation is the ability of the voltage to remain between the upper and lower limits [NRS 048-2, 2006]. The aim of calculating the voltage drop when designing LV feeders is to ensure that there is a high probability the voltage supplied will stay within acceptable levels, majority of the time [Heunis and Herman, 2003]. The worst case with regard to network design is the load that leads to the most severe voltage drop. Principal practice for calculating voltage drop is based on the assumption that the maximum voltage drop coincides with the maximum load drawn by connected consumers. This assumption has lead to the load models previously discussed typically being used to model load conditions at the time of maximum demand for voltage calculations. This could be a result of an increase in demand, voltage unbalance or both [NRS 034-1, 2007]. As a result there have been cases where the assumption that maximum voltage drop occurs at the maximum loading conditions has been found not to be strictly correct [Gaunt, 1999].

QoS standards provide the limits, time and measurement parameters to evaluate voltage quality. So far the voltage regulation based on load magnitude and behaviour (NRS 034-1) and QoS criteria (NRS 048-2) have not been merged to develop a new set of characteristic design parameters.

Heunis and Herman [2003] compared two sets of design criteria, one based on voltage regulation criteria and the other QoS criteria. Probabilistic methods were used to design for each criterion. It was found that feeders designed to meet voltage regulation criteria were prone to violating QoS criteria. Also it was found that the probability of QoS violation decreased for an increasing number of customers connected on the feeder. Shorter feeders and high income communities were also found to be prone to QoS violation. For the short feeders, it was observed that QoS violations were reduced when the number of customers connected to the feeder increased. This was due to the randomness of the load decreasing because of the increased number of consumers, illustrated by a decrease in the standard deviation of the loads [Heunis and Herman, 2003]. No explanation was given for why high income increased the risk of QoS breach. QoS compliance analyses carried out in electrified South African townships found significant non-compliance in the existing networks and this was attributed to the lack of understanding in linking loads, voltages, design and QoS standards [Gaunt and Herman, 2011].

The question now is "what is the most appropriate parameter(s) to use as an input which coincides with maximum voltage drop"? Gaunt [1999] recommends that the maximum μ/C and the mean of α calculated from the highest 60 loads be used as the load parameters for voltage drop calculations. But this suggestion still does not merge the voltage regulation conditions of NRS 034-1 to the QoS criteria of NRS 048-2.

2.5 SOUTH AFRICA'S LOAD RESEARCH PROJECT

In 1992 a paper, [Herman, 1992], was published aimed to motivate positive action to be taken in addressing problems associated with LV network design in South Africa. This paper highlighted four main problems that were affecting the derivation of useful design guidelines to be utilized by South Africa's LV network designers.

The problems listed were:

a) **Lack of relevant and statistically reliable load data**

This problem was considered to be the most significant cause of the inadequacy of the then design guidelines.

b) **Coarse customer classification**

In the year of publication of this paper, 1992, the design guidelines were only based on 3 customer classes:

- High income
- Middle income
- Sub economic

c) **Inadequate guidelines being used**

The then existing guidelines were largely based on British and European practices. Besides the fact that the material upon which these guidelines were based was dated, differences in social behaviour patterns and the use of alternate forms of energy between the Europeans and Southern Africans, greatly impacted load patterns and thus design parameters.

d) **Absence of a single, independent authoritative body whose purpose would be to formulate and publish guidelines**

This resulted in variation of guidelines and methods employed by the engineers involved in LV network design as there was great uncertainty which was the by product of numerous groups attempting to have power over the documenting and issuing of guidelines.

A load research program had been launched in 1987, prior to the publication of this paper, and was backed financially by the National Energy Council of South Africa (NERCSA). The intent of this research program was to establish new design guidelines based on load behaviour characteristic to South Africa as it had been established that the existing design guidelines for LV network design based on British practices were not adequate [Herman, 1992]. In fact, prior research conducted by Herman [1989] showed that despite similarities in load profiles, predominantly on weekdays, the different distribution practices between South Africa and the UK affected the consumer’s maximum demand.

These practices include:

- Circuit breaker tariffs (Current limiting circuit breakers maybe installed)
- Load limiting relays (Restrain hot water cylinders form operating whilst stove is switched on)
- Central water heater control
- Four core cables

These activities are practiced methods in South Africa but not necessarily in the UK. These factors affect the maximum demand of the consumer and thus design parameters applicable in the UK may not satisfactorily represent the maximum demand in South Africa.

Population growth in South Africa’s urban areas, at that time, was estimated to require approximately 200 000 new homes to be built annually. This drove the urgent requirement for accurate and economically acceptable design figures and hence the need for an extensive load research project which addressed the continually changing behaviour of domestic loads in order to cope with these future demands.

2.5.1 South Africa's national load research program

A load research program was launched in South Africa in 1988 because prior design standards did not accurately represent the country's actual consumer loads [Herman, 1992, Dekenah, 2006]. Data loggers were used to synchronously record currents drawn by independent households. The makeup of the data loggers is reported in [Herman and Gaunt, 1991].

Figure 2.12 shows how the loggers were typically placed on the feeders. The data loggers were placed in a manner as to record the electrical current drawn by individual households. The neutral current was not recorded. The reason is quoted as being that "*during the 5 minute period the current in the neutral changes in both magnitude, which can be recorded easily, and angle which cannot. As a result it is neither practical nor useful to measure currents in the feeder neutral*" [Gaunt et al, 1999].

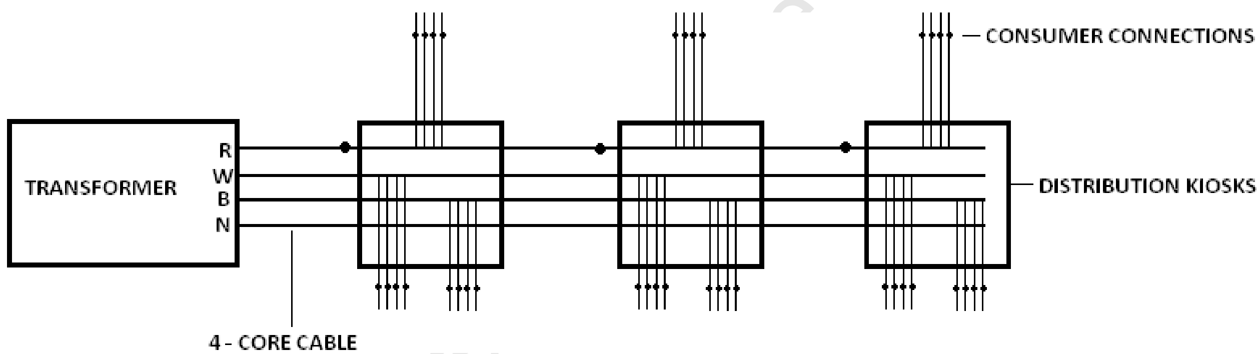


Figure 2.12: Typical placement of sensors [Herman and Gaunt, 1991].

Socio-economically homogeneous groups of customers were logged based on the assumption that they represented a typical load class. It was presumed customers living in the same community were in the same socio-economic class and therefore in a similar load class.

The sample size required to establish statistically acceptable results was determined using equation 2.4.

$$N = \frac{Z^2\sigma^2}{e^2} \qquad \text{...Equation 2.4}$$

Where:

N = required sample size

Z = Probability density factor

σ = Standard deviation of pilot sample (26 customers)

e = Tolerable error.

Currents were recorded at a 2 second sampling rate and averaged over a 5 minute period. The South African quality of supply standard dictates voltage regulation be assessed over a 10 minute period. The 5 minute averaging period was based on the Nyquist sampling theorem were the averaging period should be at least half of the assessment period [Herman, 1993]. In the context of voltage drop calculation Sellick [1995, as cited by Sellick, 1999] found that changing the averaging period from 1 minute to 5 had no significant impact on the calculated output.

The load research program became national in 1994. A minimum of 60 customers were monitored at a site in order to reduce the sampling error to values below 1A. The data loggers were moved to new sites every 2 years. In some instances the loggers were left for longer periods in order to increase sampled data to be utilized in longitudinal studies [Gaunt et al, 1999]. But, as with most real world data, there were various sources of error. These were identified by Gaunt et al [1999] to be due to:

- Channel breakdown in the data logger resulting in either a high or almost zero value.
- Defective connections between the current transducer and logger,
- Error in data transmission between the logger and laptop during data collection,
- Awareness of the loggers could psychologically affect electricity usage of customer.

These errors may manifest as deviations from actual consumption values or ‘data holes’ which are defined as an absent data slot on one logger which appears on another logger carrying a reading for that time [Sellick, 1999]. Compensating for the deviations or lost data can compromise the accuracy of the data. The possible methods of dealing with the bad data will be discussed in the next section.

2.6 CONCLUSIONS

In conclusion, the literature review has highlighted the following factors:

- Statistical analysis is important to carry out voltage calculations and load modelling to achieve the most accurate results. The Beta pdf appears to be the strongest representational distribution.
- QoS standards are consensus driven and leave many criteria open to interpretation. For example**:**
    - There is no indication when in the year the 1 week period required for compliance assessment is to be selected,
    - The period over which load data used for QoS assessment is averaged has been picked without much consideration of the impact of data resolution on the QoS assessment.
    - The implications of risk associated with the stochastic variation have not been factored into the compliance and limit levels.
    - There is an obvious link between probabilistic methods of calculating voltage drop and QoS specifications.
- The Herman-Beta method of voltage calculation is superior to other analysis tools with which it has been compared and no other methods of probability based voltage drop calculation have been identified. It is more sensitive to the parameters on which voltage drop is reliant.
- The Herman Beta method is dependent on representative input parameters to accurately predict voltage drop performance of the feeder(s).
- There is a need to incorporate QoS criteria into design parameters in order to ensure that the designed LV networks operate within QoS guidelines. The key tools for integrating design and QoS limits appear to be the Herman-Beta algorithm and the BPP.
- There is a large database of measured data available which can be used for the analysis to be carried out in this investigation.

3

THEORY DEVELOPMENT

In chapter two the pros and cons of the techniques for modelling load and calculating voltage drop across LV feeders were discussed. QoS measurement methods as dictated by QoS standards were also discussed. From the literature survey it is apparent that there has not been much work done into translating QoS measurement methods, defined in the standards, into actual usable design parameters. Also there has been no clear reason given to the choice of some of the QoS measurement parameters. QoS compliant design parameters will be developed in this thesis based on the voltage regulation conditions of NRS 048-2 and load. To achieve this it is necessary to select:

- a suitable design model that is capable of dependably representing residential load, and
- a voltage calculation technique that can predict the expected voltage along a feeder accurately.

This chapter discusses the theory upon which the research methodology will be based. Along with selecting an appropriate load modelling and voltage estimation technique, the following topics related to QoS assessment will also be discussed:

1. Assessment period,
2. The implications of design risk on the QoS 95% compliance standard
3. Determining a suitable averaging time for load data
4. Customer classification approaches and
5. Statistically suitable sample sizes

3.1 LOAD MODELLING AND VOLTAGE REGULATION

3 major load modelling techniques were argued in chapter two which are the deterministic, probabilistic and bottom-up load models. Deterministic modelling encompassed by the ADMD value was found to be the weakest modelling technique. This model type is focused on deriving the best estimate of maximum demand as it assumes maximum load to be the worst case condition resulting in the highest experienced voltage drops along LV feeders. This assumption has been found to not always be true. Also, the ADMD only describes the magnitude of the load without regard of the distribution of load currents of the customers at the time of maximum demand.

Although very data dependant, the probabilistic and bottom-up models can be used to represent times other than that of maximum demand. Bottom-up models require socio-demographic data that includes occupational and behavioural data in terms of appliance usage for each household. South Africa's load research project has accumulated over 10GB of household level load data. This data is not sufficient to produce a bottom-up model but lends itself well to use for probabilistic modelling. Probabilistic models have been found to be highly representative of load as they take into account the stochastic behaviour of load. According to Herman [1993] in order to make a useful model a statistical load model must be constructed in a manner that makes it applicable to LV distribution network design [Herman, 1993]. Herman and Gaunt [2007] state that "*Load parameters should quantify the statistical characteristics of the stochastic behaviour of the customers in a format that can be manipulated in the design calculations. This usually requires load parameters that express the mean value as well as a measure of the dispersion of the loads of a given group of customers connected to the network*." This task is best handled by probabilistic modelling which is possible due to the availability of the South African load database

3.1.1 Probabilistic models

From literature the most popular pdf functions used to trend load were found to be the Gaussian, Beta, Log-normal and Gamma probability functions. Out of the 4, the Beta pdf was found to be the most flexible function to model load behaviour as their characteristics lend themselves well to mimicking load current dispersions and magnitudes.

Another attribute of the Beta function is that the Herman beta voltage drop calculation method, the significance of which is discussed in the next section, takes in an input load model represented by the Beta parameters α, β and c.

It is also the foundation of the BPP which is a very useful tool to find the load conditions, in terms of both load magnitude and dispersion, which lead to the actual worst case voltage conditions along a feeder. This is because with the BPP it is possible to simultaneously plot numerous load points each representing a single period and forming a pattern that depicts the voltage drop. Since the NRS 048-2 document calls for a minimum assessment period of 1 week which translates to 2016 points, the BPP would be a powerful tool to use for comparative analysis of the different points which if attempted using the regular continuous pdf arrangement, becomes illegible.

<u>THE BETA PARAMETER PLOT</u>

By rearranging equations 2.3 and 2.4 Gaunt [1999] derived the following relationship between α and μ/C.

$$\alpha = -(s^2 - 1)\frac{\mu}{C} + s^2 \qquad \text{...Equation 3.1}$$

Where:

s = slenderness = μ/σ=1/γ and γ is the coefficient of variation.

The slenderness, s, indicates the dispersion of loads. It is dependent on the homogeneity of customer behaviour. The slenderness, s, tends to be high when load is limited by means such as circuit breakers and in instances where customers tend to behave in a similar manner at the time of maximum demand. If customer behaviour is unlimited s values are lower.

An error in the derivation of equation 3.1 was found and corrected in this investigation. The following corrections were applied to correct the mistake.

$\alpha = \frac{\mu(C\mu - \mu^2 - \sigma^2)}{C\sigma^2}$ …Equation 3.2

$$\alpha = \frac{C\mu^2}{C\sigma^2} - \frac{\mu^3}{C\sigma^2} - \frac{\mu\sigma^2}{C\sigma^2}$$

$\alpha = \frac{\mu^2}{\sigma^2} - \left(\frac{\mu}{C}\right)\frac{\mu^2}{\sigma^2} - \frac{\mu}{C}$ …Equation 3.3

Substituting equation s = $\frac{\mu}{\sigma}$ into equation 2.2.4

$$\alpha = s^2 - \left(\frac{\mu}{C}\right)s^2 - \frac{\mu}{C}$$

$$\alpha = -\left(\frac{\mu}{C}\right)s^2 - \frac{\mu}{C} + s^2$$

$$\alpha = -\left(\frac{\mu}{C}\right)s^2 - \frac{\mu}{C} + s^2$$

$\alpha = -(s^2 + 1)\frac{\mu}{C} + s^2$ …Equation 3.4

The implications of the error will obviously include a different calculated α value but has been found not to affect the overall shape of the BPP derived from the original formula. The positions of the lines of constants on the BPP plot are altered by the change in formula. Figure 3.1 shows the position of the some characteristic slenderness lines on the BPP plot from equation 3.2 and figure 3.2 the slenderness lines from the corrected equation 3.4.

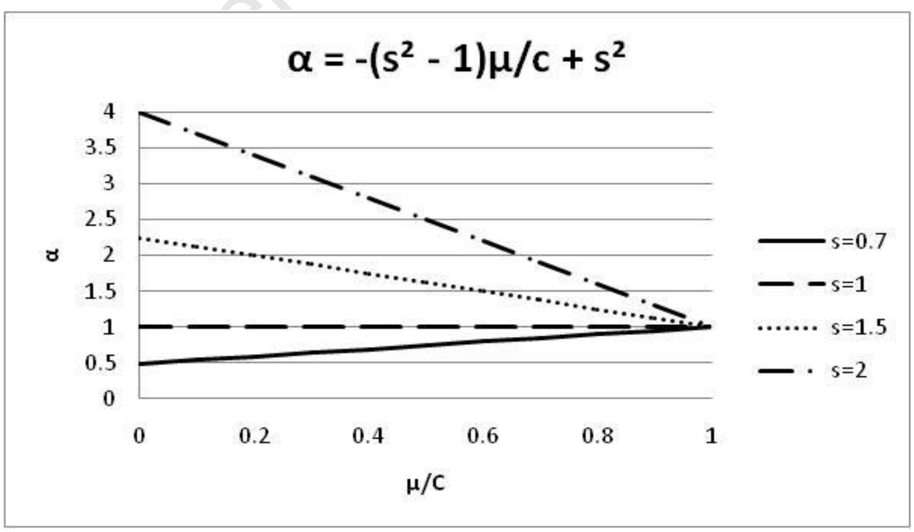


Figure 3.1:Characteristic slenderness lines as derived from the original formula $\alpha = -(s^2 - 1)\frac{\mu}{C} + s^2$

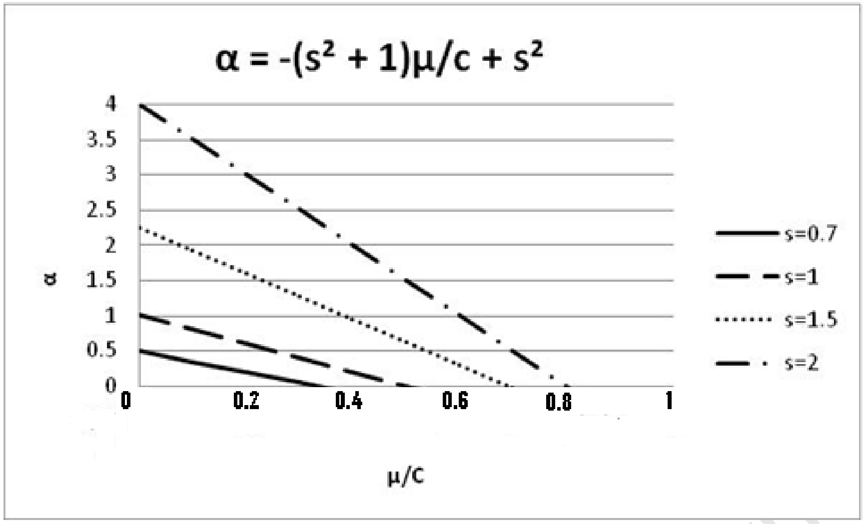


Figure 3.2:Characteristic slenderness lines as derived from the corrected formula $\boldsymbol{\alpha = -(s^2+1)\frac{\mu}{c} + s^2}$

The use of the slenderness lines for the BPPs is to compensate for the absence of the β parameter whose relationship with α indicates the skewing of the Beta distribution as depicted in figure 3.2. An advantage of the BPP is that it allows numerous instances in time, >1000, to be plotted and compared on one graph. The second advantage came from the observation that different pairs of α and β when inputted in the Herman Beta spreadsheet as load parameters (using equal confidence levels and number of customers) produced equal estimates of voltage drop magnitudes. Plotting these points on a BPP resulted in a locus of μ/c and α values resulting in equal estimates of voltage drop. This locus has come to be known as the iso-volt drop curve.

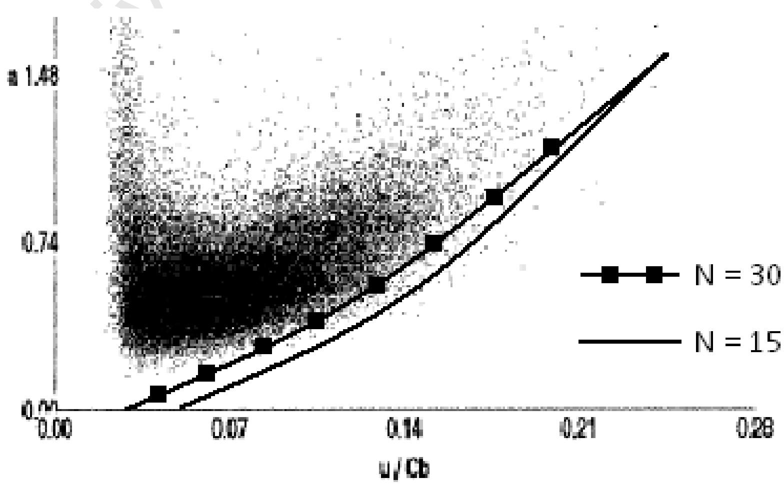


Figure 3.3: Illustration of locus of constant voltage drop on a BPP for 15 and 30 customers [Gaunt, 1999].

Gaunt [1999] worked with voltage drop values associated with the maximum demand. Figure 3.3 illustrates the concept of the iso-volt drop curve on a BPP. Points above the curve depict those that will lead to voltage drops lower than that at maximum demand and alternately those below are the points associated with voltage drops higher than that at maximum demand. All calculations are done using similar levels of confidence, number of customers, scaling factor etc. The only parameters varied in the voltage drop calculations are α and β representing the different points on the BPP.

Figure 3.3 shows that the steepness of the locus is affected by the number of customers. According to Gaunt [1999], "*the risk of voltage drop under alternative loading conditions decreases as the number of customers on the feeder increases. For an infinite number of customers the locus is a vertical line through the point corresponding to system maximum demand*." In other words an increase in the number of customers results in a lower number of points expected to lead to voltage drop predictions higher than that at maximum demand. This is because "*for a very large number of customers on a feeder, the dispersion about the mean will be balanced, the mean value will determine the voltage drop in the feeder, and the value of alpha will be insignificant*" [Gaunt, 1999]. This conclusion of the influence of a large number of customers is in line with the central limit theorem.

According to Gaunt [1999], the iso-volt drop curve is affected by:

- number of customers and nodes
- risk/confidence levels for voltage drop calculations and
- feeder topology (e.g. 3-phase, bi-phase or single phase).

<u>THE COV CURVE</u>

Finally, with regards to generalizing the derived parameters for use in other countries, the validity of the COV relationship discussed in 2.2.4 has not been tested widely. Success of the COV curve means countries can derive their own representative α and β values from known ADMD values or simply the mean, μ, and standard deviation, σ.

The COV curve can be mapped onto the BPP plot in a manner illustrated in figure 3.4 allowing the planner to derive the characteristic Beta parameters from the ADMD of the community to be electrified. However, because the original curve was not derived from real world data but rather set design parameters typical to the different income classes in Southern Africa, the relationship has to be tested in order to see if it still holds.

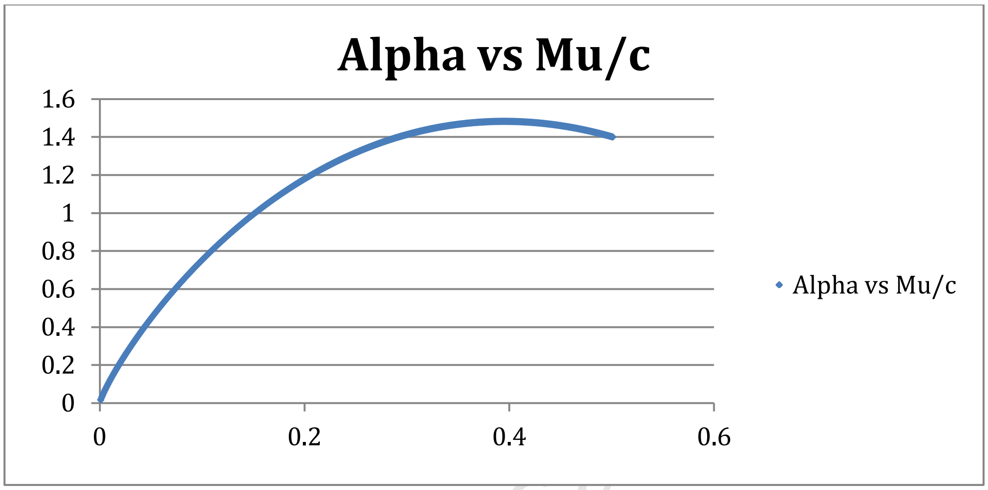


Figure 3.4: Mapping of COV curve on beta parameter plot

3.1.2 Voltage regulation

Voltage drop is a significant constraint when considering quality of supply, however, when considering conductor losses which are translated to cost, current is the dominant factor [Sellick, 1999]. Gower [1994 as cited by Sellick, 1999] observed that an overdesign level of at least 15% was experienced, when only looking at the voltage drop, and not considering load growth or system losses. In relation to the cost due to losses a method was developed by Sellick [1999] which relates the cost of conductor losses to the voltage drop which also allows for a stochastically varying current in the conductor phases. Optimum conductor sizes can only be achieved by considering both voltage drop and current carrying/thermal capacity. With the European style of LV network design which is characterized by longer cables the limitation imposed by voltage drop on conductor sizing increases. This is due to the fact that voltage drop is a function of length [Sellick, 1999]. Also, when dealing with grouped domestic load, voltage drop is of more significance than the thermal capacity parameter [Herman and Kritzinger, 1993].

Load flow analysis methods are not applicable for voltage drop calculations for residential networks, due to the stochastic nature of residential load which require a statistical approach [Sellick, 1999]. From the literature surveyed in chapter two, the Herman Beta method is the most accurate of the existing voltage calculation algorithms available and it thus the best technique to calculate voltage drop for this investigation. It incorporates statistical analysis based on a Beta model of load and calculates voltage drop probabilistically. But because it is a statistical method it is coupled with a design risk. The implication of design risk on voltage drop violations is illustrated in the shape of the iso-volt drop curves on a BPP in figure 3.5.

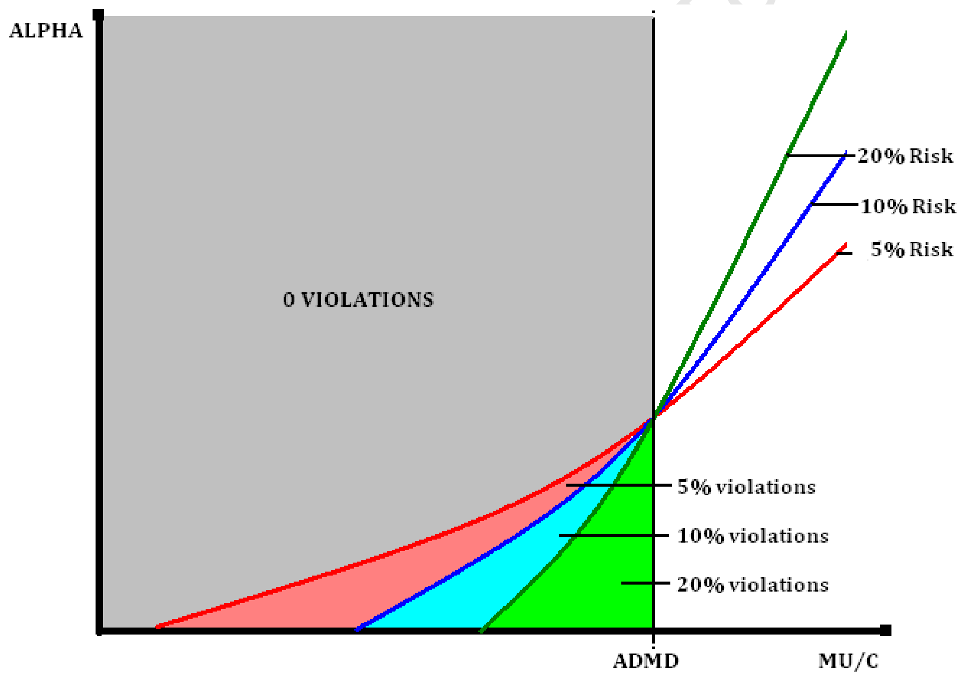


Figure 3.5: Concept of IVD curves based on the voltage drop at ADMD as they apply to varying risk levels on a Beta Parameter Plot.

The number of voltage violations expected for 3 communities based on the data recorded for the communities over a period of one year were calculated and are provided in table 3.1. The Herman Beta algorithm was used to calculate the voltage drops and the IVD voltage drop was set to be that at the ADMD. Voltages surpassing this value were deemed to be violations. From the results and as expected the number of violations decreases with an increasing level of risk.

Table 3.1: Expected voltage drop violations for one year for three communities calculated at 5%, 10% and 20% risk

INCOME GROUP	**COMMUNITY**	**Period**	**5% risk**	**10% risk**	**20% risk**
low	Tambo	2003 (Jan– Jun)	384	331	280
	Tambo	2003 (Jul – Dec)	279	261	134
Middle	Westridge	2004 (Jan– Jun)	168	112	44
	Westridge	2004 (Jul – Dec)	153	90	20
High	Moreletta	2003 (Jan– Jun)	0	0	0
	Moreletta	2003 (Jul – Dec)	6	4	3

The results show that a lower number of voltage violations are expected in the higher income groups. The reasons will be investigated in chapter 5. The compliance criterion of NRS 048-2 however dictates that the highest and lowest of the assessed 95% weekly values over the full measurement period shall not be outside the compatibility levels or the otherwise contracted voltage deviation. The implication of the selected value of design risk on achieving the 95% quality compliance required by NRS 048-2 must be considered. In other words, when basing voltage drop calculations on a particular risk how can the risk be incorporated into the violation assessment in order to maintain the required 95% compliance? To maintain 95% overall compliance the number of permissible voltage drop violations would have to be altered in relation to the level of risk used for the calculations. This relationship between risk and violations was calculated using equation 3.1 which is based on the principle of multiplying fractions or alternately percentages.

$$\text{QoS Compliance } \times \text{Design Confidence} = 0.95 \text{ p.u.} = 95\% \qquad \text{...Equation 3.1}$$

where:

$$\text{QoS Compliance} = 1 - \text{violations} \qquad \text{...Equation 3.2}$$

$$\text{Confidence} = 1 - \text{risk} \qquad \text{...Equation 3.3}$$

$$\text{Total Compliance} = \text{Overall Compliance} = 0.95\text{p.u.} = 95\% \qquad \text{...Equation 3.4}$$

According to equation 4.1, the current practice in South Africa of using 10% risk (90% confidence) to calculate voltage drop is incorrect as it would lead to an overall compliance level of 90%, with the constraint that no violations are permitted. If violations are allowed, the overall compliance will be lower than 90%. Both conditions are out of the 95% quality compliance criterion of NRS 048-2 and are therefore in violation of QoS rules. Therefore according to equation 3.1 the allowable design risks are confined to values of 5% and below.

The Herman Beta algorithm does not permit for 0% risk. Therefore in keeping with equation 4.1 a combination of design risks and violations provided in Table 3.2 will be used for the study. The intention is to investigate how to achieve 95% overall compliance during the assessment period while having a level of freedom to alter the design risk. The assumption is that all combinations will result in the same design point being derived.

Table 3.2: Combination of design risk level and the associated maximum permissible voltage violations to maintain 95% overall compliance.

Risk (%)	Allowable violations in assessment period (%)	Number of allowable violations in 1 week	Overall Compliance (%)
0.1	4.9	99	95
2.5	2.56	52	95
5.0	0	0	95

3.2 SELECTING THE ASSESSMENT PERIOD

The period or season during which the assessment period is to be taken is not defined in the QoS standard. This implies that it is assumed that each day of the year holds an equal chance of experiencing a voltage violation, in which case picking any random week to measure voltage drop compliance is valid. This assumption does not fall in line with the fact that demand magnitudes and dispersion are affected by time factors such as seasons of the year. The dependence of domestic load on seasonal variations implies there is a more suitable period during the year to assess QoS compliance which is most prone to voltage violations. For example during winter electricity consumption is typically higher than the other seasons because of the need of electric heating, central heating systems, more cooking, higher residential occupancy etc prompted by the low temperatures [Wright and Firth, 2007], although in other communities loads might be higher in summer.

To illustrate the need to define the period of the year from which the assessment period is to be drawn and also to find the most appropriate period to take the sample week, voltage drop violations were calculated for a year using the measured load currents for 3 communities. The voltage drop experienced at maximum demand was set at the compliance limit and voltage drop was calculated at 10% risk (90% confidence) in accordance to current practice. Similar to calculations in section 3.1.2, violations were defined as voltage drops surpassing that at maximum demand. Table 3.3 shows the results.

Table 3.3: Monthly voltage violations for low, middle and high income communities at 10% risk, c=60A.

MONTH	MORELETTA	TAMBO	WESTRIDGE
January	0	17	4
February	0	87	18
March	0	130	18

April	0	146	104
May	0	4	24
June	0	0	0
July	4	0	0
August	1	6	0
September	0	261	78
October	1	0	67
November	0	3	6
December	0	9	2

Table 3.4: Month of maximum demand of the communities

Community	**Period**	**Month of Maximum demand**
Tambo	2003 (Jan – Jun)	April, 2003
Tambo	2003 (Jul – Dec)	September, 2003
Moreletta	2003 (Jan – Jun)	June, 2003
Moreletta	2003 (Jul – Dec)	October, 2003
Westridge	2004 (Jan – Jun)	April, 2003
Westridge	2004 (Jul – Dec)	September, 2003

It was found that the maximum frequency of voltage drop violations occur around the period of maximum demand. Although demand magnitude has been found not to be the sole contributor to voltage drop magnitude it is clearly a significant contributor. Therefore for this investigation the assessment period of one week will be defined as that within which the maximum demand occurs. This will be made up of the day within which the maximum demand of a community occurs and the 3 days before and after it. This one week period translates into 2016 five minute intervals. The assessment week will therefore also be referred to as the week of maximum demand in this report.

3.3 LOAD DATA ANALYSIS

3.3.1 Dealing with bad data

The loads for about 40 communities have been recorded. A SQL database of load data has been prepared in Microsoft Excel for easy access. From inspection, deviations in load and almost zero errors resulting from the error sources discussed in section 2.5.1 are not easy to distinguish from actual data; however, a -999 value is used to represent a data hole. The data spreadsheet format is shown in figure 3.6. Each column shows currents drawn by a particular household throughout the recorded period and each row shows the currents drawn by all measured households in the community during a specific five minute period. The files are separated by community name and each file is made up of either the first or last 6 months of the year. The number of columns in each file are typically 52,128 for the first semester of the year and 52,992 for the second totalling 105,120 rows of load currents averaged over 5 minute intervals for each measured household for the year.

COMMUNITY A							
	1000369	1000370	1000371	1000374	1000376	1000377	1000383
1/1/2003 0:00	-999	-999	-999	2.603	0.022	0.022	0.846
1/1/2003 0:05	-999	-999	-999	2.55	0.021	0.021	0.847
1/1/2003 0:10	-999	-999	-999	2.6	0.024	0.024	0.845
1/1/2003 0:15	-999	-999	-999	2.633	0.023	0.024	0.849
1/1/2003 0:20	-999	-999	-999	2.598	0.023	0.023	0.852
1/1/2003 0:25	-999	-999	-999	2.602	0.023	0.024	0.85
1/1/2003 0:30	-999	-999	-999	2.634	0.024	0.024	0.851
1/1/2003 0:35	-999	-999	-999	2.635	0.023	0.023	0.85

Figure 3.6: Data format for a recorded community

There are 4 main methods which can be used to deal with these data holes. Sellick [1999] heeds that "*correct error removal from the data can be assumed only it the software developed is error free and if the chance of the exclusion of a 'good' consumer channel is less than the chance of inclusion of a 'bad' consumer channel*." In other words, the method to compensate or eliminate errors should not cause more problems than it solves.

-999 values were replaced by "e" in the excel files so that the error does not hold a magnitude that could create miscalculations if any of the following techniques is applied.

1. Exclusion of bad data

   This approach involves simply ignoring the data holes and excluding them from the data set. The obvious advantage of this technique is that the data is not altered through assumptions that would be used to create figures to fill in these blanks. Disadvantages include the reduction of the sample size every time a data hole is encountered and the severity of the reduction of the sample size is proportional to the prevalence of errors in the data file.

2. Interpolation

   With this technique errors are averaged out using surrounding values. An example is given in figure 3.7.

Date and time	1	2
12/1/2010 0:00	0.04	0.03
12/1/2010 0:05	e	0.04
12/1/2010 0:10	0.06	0.04
	BEFORE CORRECTION	

Date and time	1	2
12/1/2010 0:00	0.04	0.03
12/1/2010 0:05	0.05	0.04
12/1/2010 0:10	0.06	0.04
	AFTER CORRECTION	

Figure 3.7: Example of interpolation

This method appears promising when dealing with a few errors that rarely occur in the data. The problem comes when multiple errors occur in the data in the manner depicted in figure 3.8 which occurs frequently in the load data.

Date and time	1	2
12/1/2010 0:00	0.04	0.03
12/1/2010 0:05	e	0.04
12/1/2010 0:10	0.06	0.04
12/1/2010 0:15	e	0.03
12/1/2010 0:20	0.09	0.04
12/1/2010 0:25	e	0.04
12/1/2010 0:30	0.05	0.05

Date and time	1	2
12/1/2010 0:00	0.04	0.03
12/1/2010 0:05	e	0.04
12/1/2010 0:10	e	0.04
12/1/2010 0:15	e	0.03
12/1/2010 0:20	e	0.04
12/1/2010 0:25	e	0.04
12/1/2010 0:30	0.05	0.05

Figure 3.8: Example of common multiple error occurrences in data

In such cases interpolation has a higher probability of producing values that are nowhere near the actual.

3. <u>Using weighted functions</u>

It was suggested by Gaunt [2010] that the contribution of the customer to the load be calculated from the times where data is available and this weighting function be used to generate a reading to replace the error. The major problem with this approach is that it can lead to the assumption that a consumer contributes equally to the overall load at different times of the day and or times of the year depending on the data the weighting function is based. Also finding a weighting function for each household that experiences a data hole during the measurement period can become very involved based on the frequency of occurrence of data holes in the data.

4. <u>Averaging</u>

The forth proposed solution in dealing with errors is simply calculating the average current drawn at that at that time interval or similar time slots and assigning that valued to the error point. This technique holds the same disadvantages as those posed by the weighted function method as it assumes customers act similarly in different time periods.

Clearly all four methods come with their own advantages and disadvantages. The most appropriate method will be the one that would produce less inaccuracy than the errors themselves. Methods 2, 3 and 4 involve assuming values to replace the error which could end up being over or under-estimates that could distort either the value or time of occurrence of the maximum demand. The method that will be used to deal with the data holes will be decided in section 3.2.2.

3.3.2 Sample sizes

The issue that arose in section 3.2.1 was that of decreasing sample size caused by data holes. Methods of dealing with the data holes were discussed but the concern of implementing these measures was compromising the integrity of the data. Sample size contributes to the degree of skewing of the distribution of domestic load currents. The skewing, which is a measure of load current dispersion, has been found to factor into the magnitude of voltage drop.

For as few as 100 customers a group of 30 – 50 customers can yield statistically stable results as long as they belong in the same customer class [Bary, 1945]. This idea is exploited when measuring real world data as it reduces the need and consequently the capital required to measure demand for the entire community, as was done during the load research project. Reducing the sample size too much however compromises accuracy [Elexon, 2005]. For samples of less than 50 it is advised that the upper limits be treated carefully as they may not be indicative of the true population characteristics [Sellick, 1999]. Richardson et al [2010] support using a large sample as a basis of developing a successful load model stating that "*For effective network modelling, large numbers of dwellings must be considered at once and the demand model must appropriately represent the time-coincident demand between different dwellings*". In the absence of large sample sizeLane [1994] suggests extending the data capturing period as a measure of compensation. Sellick [1999] argues that such an approach would lead to misrepresentative results due to the use of a small sample size and increasing the period will not necessarily alter this misrepresentation. It can be argued though that if the standard deviation of the community is small representing a small variation in usage between customers, the effects of a small sample size on accurately representing the measured community is reduced [Herman, 2010].

The different methods available to deal with the data holes can deal with the problem of sample size but alter the data compromising its integrity. Therefore the data holes will be ignored (Section 3.2.1, method 1). To deal with the issue of sample size, any period containing a sample size of less than 30 will not be considered. In cases were the sample size is slightly less than 30 for a small number of 5 minute intervals interpolation maybe considered. If interpolation is used the periods it was applied will be indicated.

3.3.3 Averaging time

Although the available load data is averaged over a 5 minute period, NRS 048-2's quality of supply measurement methodologies are based on 10 minute data. As an extra constraint not more than two consecutive 10 minute values are allowed to exceed the higher applicable compatibility levels or the otherwise contracted voltage deviations. This requirement serves to ensure that exceedance of equipment design standards are avoided for long periods in the week (e.g. during peak network loading)

Using half hourly load data has been found to be sufficient when generating load profiles for billing [Elexon, 2005] as well as when dealing with loads aggregated over a high number of customers such as those at transformer level [Wright and Firth, 2007]. However, 30 minute data resolution does not show high frequency variations in the load in individual households [Ibid]. Lane [1998 as cited by Wright and Firth [2007] and Stokes et al [2004]] both used half hourly load data to model the LV load. Typically load data is collected at 1, 5, 10, 15 or 20 minute intervals [Wright and Firth, 2007]. Comparing with 2 minute data, Herman and Kritzinger [1993], as previously mentioned in chapter 2, found 5 minute data to be adequate for load modelling purposed for network design when dealing with the effect of averaging time on the ADMD value.

Wright and Firth [2007] investigated the impact of time averaging on the statistical calculations. Data collected at 1 minute intervals from 7 households in England over long periods was used to represent true load. Using this data 5, 15 and 30 minute data was generated. According to Wright and Firth [2007] "*arithmetically averaging loads collected at one period over longer periods is precisely equivalent to actual logging over such longer periods. For example, averaging power or aggregating energy from 1-min data over 5-min intervals gives the same numbers (ignoring logging errors) as logging at 5 minute intervals.*" Using the different averages the results in table 3.5 were obtained.

Increasing the averaging period was found to reduce the standard deviation of the measured loads but did not impact the mean. The result that the mean was not affected is in contradiction to the findings of Herman and Kritzinger [1993] where averaging periods greater than 5 minutes were found to significantly reduce the ADMD. Widen et al [2010] carried out a similar study to that of Wright and Firth using 10min and 60 minute data recorded for 13 Swedish households. With hourly averages the maximum power drawn by each house was lower and the minimum power was higher in comparison to corresponding powers recorded for 10 minute data. The impact of averaging on the maximum and minimum recorded loads for each household was found to vary in intensity between different households but, similarly to Wright and Firth [2007], the standard deviation was also found to decrease with increasing averaging time.

Based on the findings of the previously discussed papers, using 10 minute data may not be appropriate for identifying the closest to actual power quality expected on the LV network. Therefore, in this investigation the effect of different averaging intervals on the new design parameters will be investigated. Since the South African load data is averaged over 5 minutes the time divisions that will be investigated will be 5 minute, 10 minute and 20 minutes. The 10 minute and 20 minute data will be derived by averaging the 5 minute data in the manner described by Wright and Firth [2007]. A rolling average method will be applied. This means that for the 5, 10 and 20 minute data the one week assessment period will still constitute 2016 time intervals. Therefore the number of violations required to maintain 95% overall compliance will be the same for all averages.

3.4 CUSTOMER CLASSIFICATION

A customer class is defined as "*a subset of customers whose distinction as a subset helps identify or track load behaviour in a way that improves the effectiveness of the forecast*" [Willis, 1996]. According to Hamilton [1944] "*A number of load curves may be added to determine some characteristics of a composite load from known values of the individual loads which comprise it*". This allows for real-world load curves within a certain load class to be appended and a general model developed for that customer type [Sellick, 1999].

Classification has been found to notably affect the coincidence factor [Bary, 1945] and coarse customer classification was attributed as being one of the factors contributing to the difficulty of developing correct design guidelines in South Africa [Herman, 1992]. In 1992 only three customer groups were used to classify different customers. These customer groups included high income, middle income and sub economic classes. In the same year Britain/Europe was reported to have had 40 customer classes. All in all, there must be a limit to the number of consumer classes defined for the sake of practicality as successful models have been developed using as few as four customer classes [Willis, 1996].

Chicco et al [2003] define a customer class as a grouping of customers according to their electrical behaviour, activities or commercial codes. The current Living Standards Measure (LSM) method of classification currently used in South Africa is based on classifying customers into 8 separate classes based on household income, dwelling and road type, as well as access to piped water and use of electrical hot water cylinders [NRS 034-1, 2007]. This method of classification may be prone to overlapping i.e. customers of different electrical behaviours may be grouped in the same class. However, as Herman [1992] observed, having more than three classes of consumers with specific distinctions reduces the risk of overlapping.

In the liberalized electricity market competing utilities, having free rein to alter tariffs, have taken to grading customers according to their actual consumption [Chicco et al, 2003]. Chicco et al [2003] argue that the liberalized approach is the most effective method of classification, as it avoids making generalized assumptions on load behaviour. Instead, this more modern approach requires "*extended monitoring of customers' consumption and the adoption of suitable discrimination techniques able to isolate customer subsets which exhibit sufficiently similar electrical behaviour*" [Chicco et al, 2004]. The liberalized market approach to classification lends itself well to developing tariff structures and billing but it is not information that is typically available for an un-electrified community. Also, a community can be built up from a mixture of consumers with different load behaviours depending on the resources available and social factors associated with each house. Today the traditional methods of classification are still practiced especially in developing countries like South Africa where typically one utility holds monopoly.

The most important criteria in defining a load class according to Willis [1996] are:

- making meaningful distinctions related to load forecasting, and
- the class distinctions must be distinguishable using available data.

Sellick [1999] expanding on the statements of Rusck [1956] recognizes the following two factors as important when grouping customers:

1) Combined loads must be similar in terms of factors such as their individual maximum and minimum loads. And no one load should receive preference over the other, and
2) The effects of time i.e. day, month, season and year on the load should be relatively similar for the individual components. This allows for the identification of the period of occurrence of maximum demand for the customer class.

An approach that could satisfy the classification conditions stated by Sellick could be that suggested by Dickert and Schegner which is to rather classify customers based on appliances used shown in table 3.5.

Table 3.5: Classification of residential customers [Dickert and Schegner]

Customer type	Appliances in use				
	general	*electric stove*	*storage water heater*	*flow-type heater*	*electric space heating*
basic	x	-	-	-	-
partly-electric	x	x	-	-	-
fully-electric (boiler)	x	x	x	-	-
fully-electric (flow-type)	x	x	-	x	-
all-electric	x	x	x	-	x

Information on the households whose loads were measured during the load research program included HWC use and the average disposable income for each household in a given community. The data resolution for HWC use indicated whether there were HWCs in the community or not. The penetration levels of HWCs in a community with HWCs were not recorded. Also, there is no income data available for some of the measured communities. For these reasons splitting the measured communities into 8 income groups would result in a small sample for each class making it difficult to identify any trends within each class. Therefore the income groups will be broadly classified as low, middle and high. Heunis and Herman [2003] found that designs based on voltage regulation criteria were more prone to QoS violations when dealing with high income households. The reason however was not provided.

In order to define the 3 income groups, the average household income data that is available was deflated to 2005 Rands using the CPI (Consumer Price Index). This was done to make it possible to make direct comparisons with the income ranges for the current LSM classes. The 8 classes were grouped to make 3 income divisions, given in table 3.6, which will be used as a definition of the classes in this report. The income divisions are categorised as follows:

Table 3.6: Low, middle and high income class definitions based on 2005 Rands

Income group	Income range per household (R)
Low	0 - 1500
Middle	1500 - 8500
High	8500 - 24000

4

EXTRACTION OF QOS BETA PARAMETERS FROM RAW DATA

MATLAB and Microsoft Excel were selected as the software tools for this research. Microsoft Excel was used because the data and Herman Beta method are in Excel format. MATLAB was used in the cases where repeated calculations were required. In these cases, data would be read from Excel, calculated by MATLAB and the results written back into Excel.

Communities were classified into low middle and high income groups using the income ranges provided in table 3.6.

Each measured community has an associated α, β and c value which is characteristic to the community. These Beta parameters are representative of the load of the community at the time of maximum demand. The α and β that are calculated from maximum measured demand, μ_{max}, will be termed α_{admd} and β_{admd}.

For each measured area the new QoS design point, which will be termed α_{qos} and $\alpha_{qos(branched)}$ will be calculated. A linear test network and an asymmetrically branched test network each comprising of 6 equally spaced nodes and 24 customers connected in a COS 211 (i.e a,b,c,c,b,a, ...) arrangement will be used. The α_{qos} parameter represents the QoS design parameter for a linear feeder arrangement, figure 4.1, and $\alpha_{qos(branched)}$ is the QoS parameter derived from an asymmetrically branched arrangement , figure 4.2. This will be done in order to investigate the effect of feeder topology on the QoS design parameters.

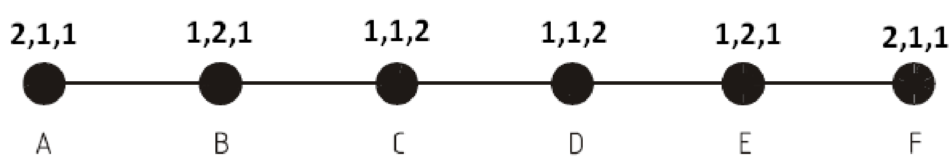


Figure 4.1: Linear feeder arrangement, COS 211 customer allocation at nodes

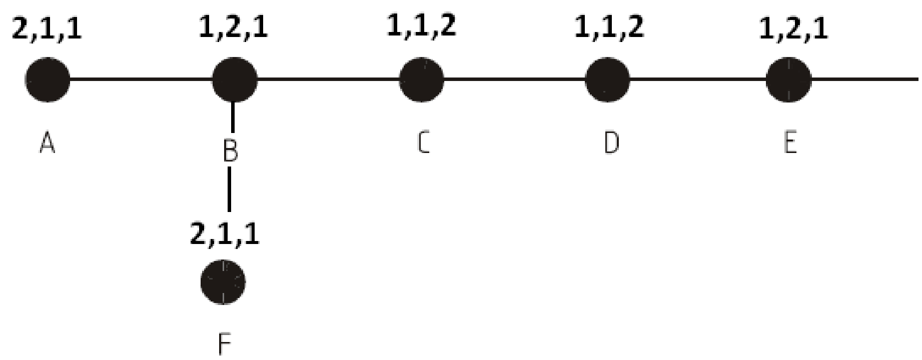


Figure 4.2: Asymmetrically branched feeder arrangement, COS 211 customer allocation at nodes

For each community, a moving average of 5 minute data was used to generate 10 minute and 20 minute averaged data and α_{qos} and $\alpha_{qos(branched)}$ parameters were calculated, from a sample week, for the 9 conditions shown in table 4.1.

Table 4.1: Conditions used to calculate QoS design parameters for branched and linear feeder topologies

	RISK	AVERAGE TIME(min)
COMMUNITY A	0.1%	5
		10
		20
	2.5%	5
		10
		20
	5.0%	5
		10
		20

4.1 SELECTING A SAMPLE WEEK

NRS 048-2 requires a minimum period be used to assess QoS compliance. In chapter 4, it was found that the maximum number of violations occurred around the time of maximum demand. Therefore the week of maximum demand, which will be termed the worst week, will be used for the analysis. This week will constitute of the day of maximum demand and the 3 days before and after it.

Because the sample sizes tend to vary due to the errors present in the data determining maximum demand by simply adding the loads of customers at each period would not be accurate. The maximum recorded demand was identified by finding the highest average calculated from the recorded demand during each time interval. The average was deemed reliable if it was calculated from a sample size > 30.

For each measured community and the sample week was selected by using the following steps:

*Step 1:*Identify the time of maximum average load using the 5-minute data. If the maximum average load is calculated from a sample size < 30 the next highest average load is selected. Steps 1 is repeated until the maximum average from a sample >= 30 is found.

Step 2: Extract the full day within which the maximum demand occurs, 3 days before it and 3 days after it to make up the week of maximum demand constituting of all 7 days of the week and 2016 points.

Step 3: Make sure all 2016 time intervals making up the week have a sample size >=30. If the sample size is <30 find the next highest recorded load current and repeat steps 2 and 3 till a healthy sample is acquired.

Steps 2 and 3 are carried out for the 5-, 10- and 20-minute data for each community.

4.2 DERIVING QoS DESIGN PARAMETERS

In order for a network to be deemed QoS compliant, NRS 048-2 permits a maximum of 5% voltage violations be experienced during the assessment period. This is the condition that will be used to calculate the αqos parameters. Because the level of risk used to calculate the voltage drops expected along a feeder determine how prone the design is to violation, different combination of risk and permitted violation were calculated in order to maintain 95% compliance. The risk-to-violation combinations are listed in table 3.2.

The voltage drop calculations will be based on a linear and asymmetrically branched feeder arrangement shown in figures 4.1 and 4.2 respectively.

Loads for each period of the worst week will be displayed on a BPP in order to exploit the IVD method to identify and quantify voltage violating points developed in [Gaunt, 1999]. There are three major shortcomings inherent in the IVD method which would not work to the advantage of this research. These shortcomings are:

1. The IVD curve is normally based on the voltage drop at maximum demand. The voltage drop at maximum demand may not generate the required amount of voltage violations necessary to find the αqos parameters.

If the voltage drop level required to construct the IVD curve that would produce the required number of voltage violations is known, then

2. the method of constructing a single IVD curve involves a large number of manual manipulation of α and β in the Herman Beta spreadsheet to obtain enough points to trend a curve. This would prove to be tedious when working with the number of communities and scenarios being investigated and could lead to inaccuracies.
3. The number of points in violation is determined by counting the points below the IVD curve. If there are numerous violations and/or if some of the load points coincide, it is difficult to accurately count the load points using visual inspection.

An alternate technique was developed to calculate the QoS parameters and is described in the following section.

4.2.1 Calculating QoS parameters

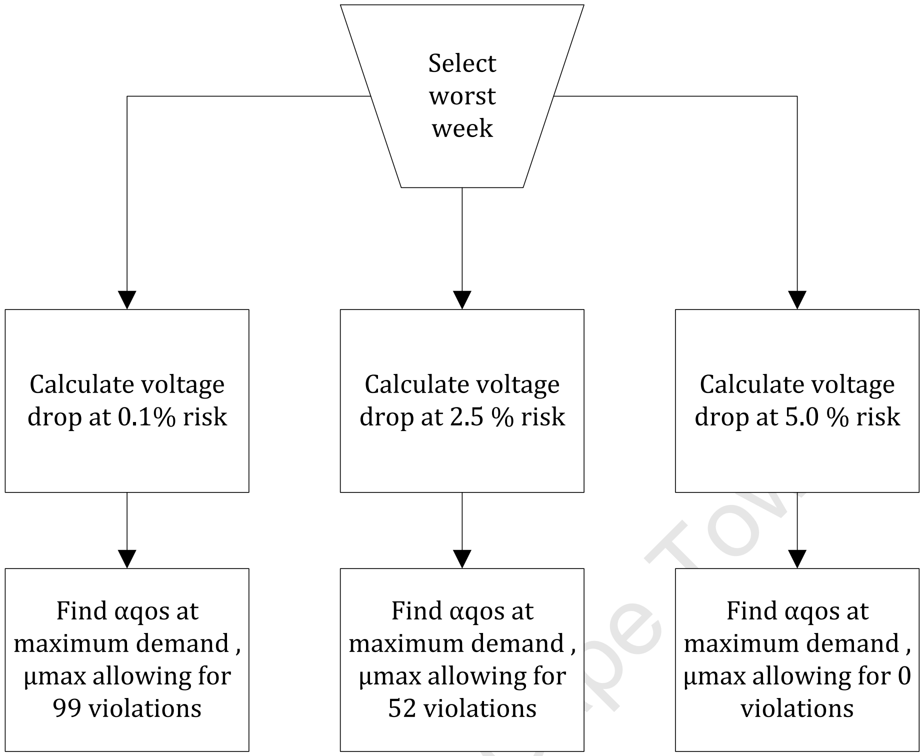


Figure 4.3: Process of calculating QoS design parameters

Figure 4.3 shows the method used to calculate QoS design parameters. All voltage drop calculations are performed using the Herman Beta method. The process shown in figure 5.3 was executed for data averaged over 5-, 10- and 20 minutes for the linear and branched feeder topologies.

The voltage drops for all 2016 time intervals in the 1 week period were calculated using the Herman Beta method. The process was automated by recording a macro in Microsoft Excel.

Having calculated the voltage drops, the QoS parameters, α_{qos} and $\alpha_{qos(branched)}$ were calculated and found using MATLAB. Any further voltage drop calculations required during this procedure were carried out using the Herman Beta method in Microsoft Excel. Figure 4.4 shows how the QoS parameters were derived.

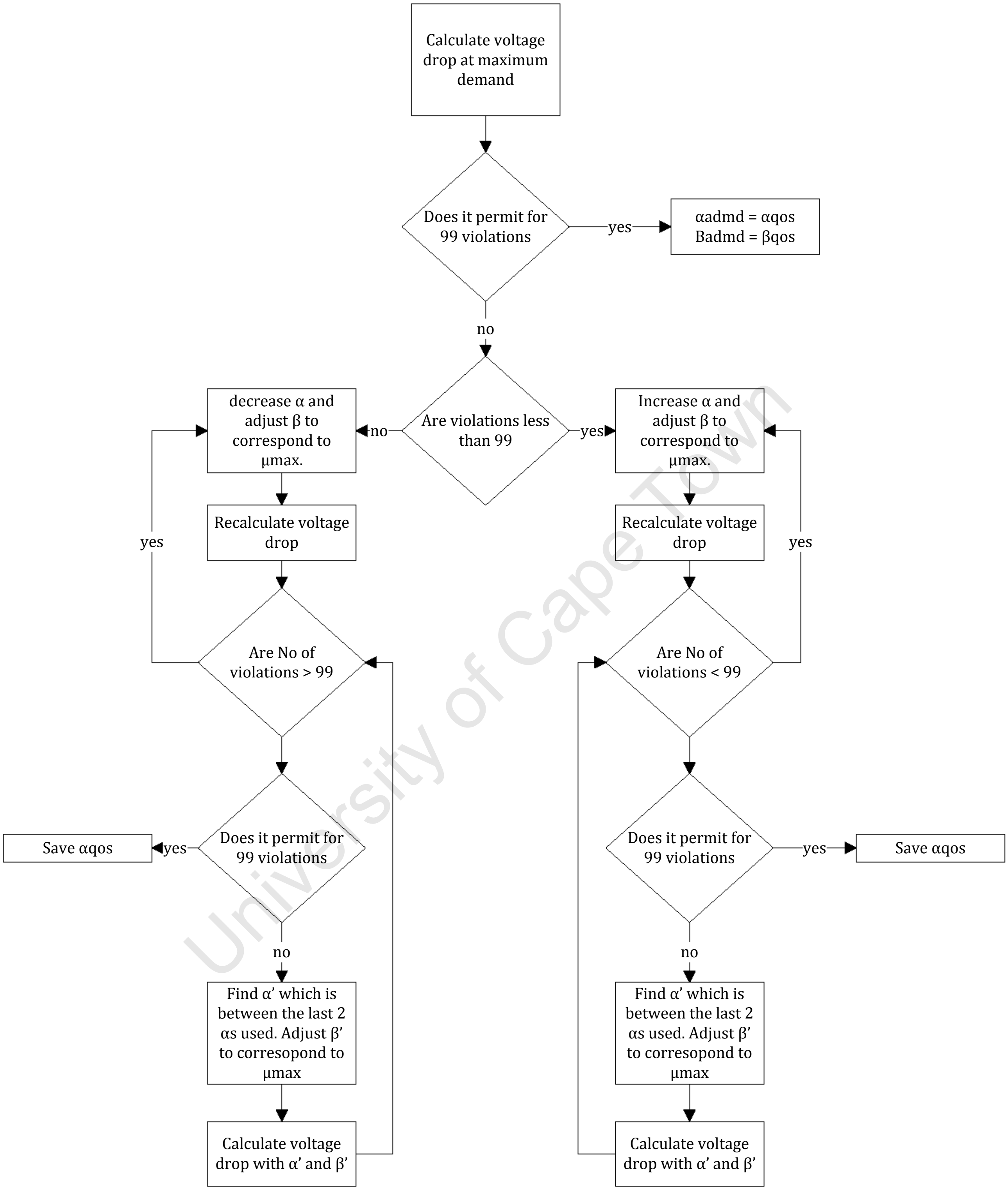


Figure 4.4: Finding QoS parameters using MATLAB and Microsoft Excel

4.3 EXTRACTED BETA PARAMETERS

The Beta parameters and information extracted from the raw data can be found in the following appendices:

- APPENDIX B: Beta parameter plots of QoS parameters
- APPENDIX C: Load profiles showing time of maximum demand and maximum voltage drop
- APPENDIX D: Tables with details of QoS parameters, maximum demand and maximum voltage drop

These results are analysed and discussed in Chapter 5.

5

ANALYSIS OF THE EFFECTS OF QOS DESIGN PARAMETERS

As previously stated, this thesis is focused on two objectives. The first is to derive design parameters that are representative of residential load, which can be used to design LV networks that comply with QoS specifications. This chapter deals with this objective. The Herman Beta algorithm is used to compare the existing standard approach (i.e. maximum voltage drop occurs at maximum load) with the approach using Beta parameters extracted on the basis of QoS. Thereafter, the effects of confidence/risk level, averaging time and income groups on the calculation of voltage drop.

The second objective is to define a means for LV network designers to distinguish the parameters appropriate for a design, based on the customer class to be electrified, which will be addressed in Chapter 6.

5.1 INTRODUCTION

"*Load estimation for urban or rural domestic consumers is very important in the cost of the electrification system. Overestimation ("safe estimate") will result in overcapitalization, while underestimation results in a poor quality of supply which could lead to expensive reinforcement later*" [NRS 034-1, 2007].

The above statement emphasizes the need for load parameters that best represent actual residential loads in order to avoid unnecessary expenses when building or running an LV network. Voltage drop calculations are performed during the design stage to predict the performance of the network being designed. Current load parameters used for the voltage drop calculations are representative of the loads at the time of maximum demand. This is because it has always been assumed that maximum voltage drop occurs at the time of maximum demand. As a result ADMD based parameters have been termed "characteristic" of residential load.

This chapter aims to show that ADMD based load parameters are not adequately representative of residential load. A different set of design parameters is introduced and argued to be more characteristic of residential load than the ADMD based parameters. These new parameters are designed to comply with quality of supply specifications and will be referred to as QoS design parameters.

5.2 EVALUATING THE PERFORMANCE OF ADMD BASED PARAMETERS

It has traditionally been believed that maximum voltage drop coincides with maximum demand. As a result, it was thought that designing for loads defined at the time of maximum demand would result in a network less likely to violate the voltage drop compatibility limits imposed by QoS standards. Therefore the ADMD or statistical parameters based on the ADMD have been used for voltage drop calculations to predict network performance. It has been found however that some networks which have been built based on the loads at the time of maximum demand experience voltage drop violations [Herman and Gaunt, 2011].

This section explores the validity of the assumption that maximum voltage drop occurs coincidentally with the maximum demand. The BPP will be used to display the loads of each community during the worst week which is made up of 2016 time intervals. Each plot will therefore constitute of 2016 load points, each representing the load during a specific period during the worst week. Each plot will distinguish the load point producing the maximum load (or ADMD) and that of maximum voltage drop from the rest of the load points. Since the Beta pdf will be used to model load, the following parameters will be used to describe these load points.

α_{admd} - Beta parameter α at the time of maximum demand

α_{Vdmax} - Beta parameter α at the time of maximum voltage drop

The Herman Beta method was used to calculate voltage drops for all 2016 load points. It was found that for a significant number of communities in the low, middle and high income classes maximum voltage drop was found to arise at times not coincident with that of maximum demand (see appendices B and C). Figures 5.1 and 5.2 show the BPP and load profile respectively for a community with non-coincident maximum voltage drop and maximum demand load points.

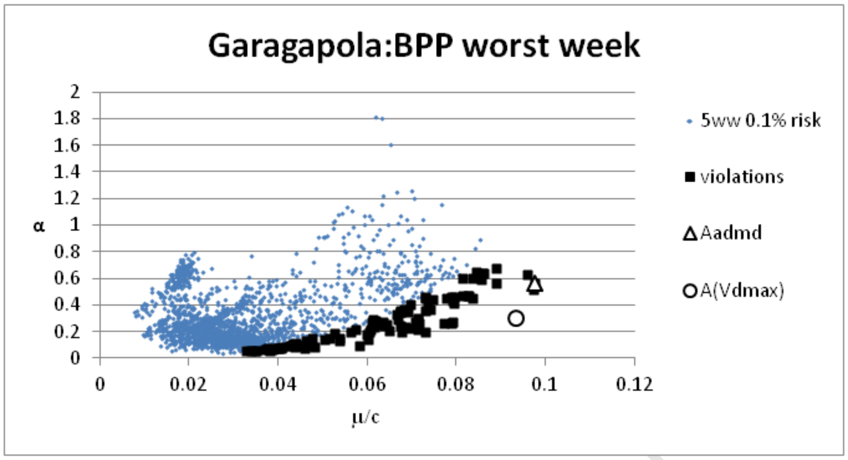


Figure 5.1: BPP for community with α_{admd} and α_{Vdmax} not coincident

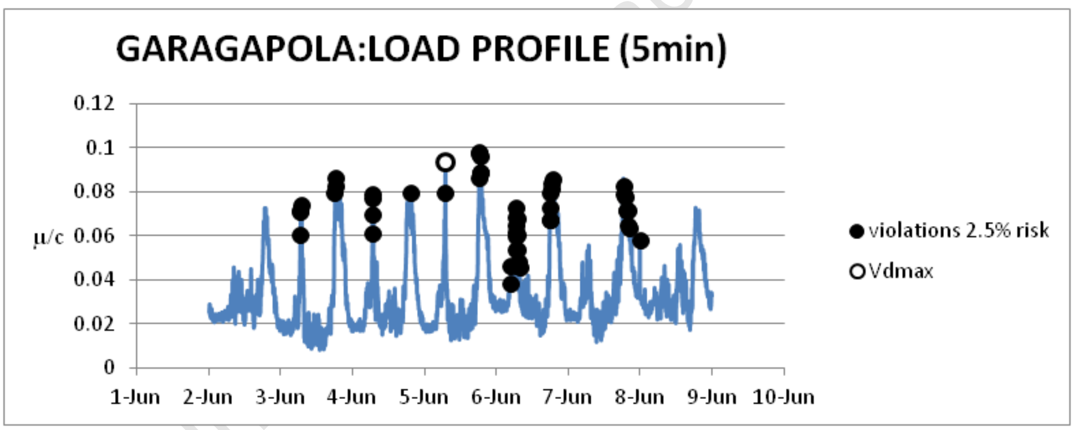


Figure 5.2: Load profile for community with α_{admd} and α_{Vdmax} not coincident

Figure 5.2 shows the time and loads at which the 51 highest voltage drops occur during the worst week for Garagapola. It is evident that the highest voltage drops are expected at higher loads but are not restricted to the maximum loads. This demonstrates that load magnitude is not the sole contributing factor to the voltage drop magnitude.

Figure 5.3 shows the Beta pdfs of the loads at the times of maximum demand and maximum voltage drop. The Beta pdf at maximum demand shows a lower degree of skewing than that for maximum voltage drop. This means that the magnitudes of load currents drawn by the households in the community at the time of maximum demand are more similar than the load currents drawn at the time of maximum voltage drop. That is, there is a higher degree of load current distribution at the time of maximum voltage drop compared to the time of maximum demand.

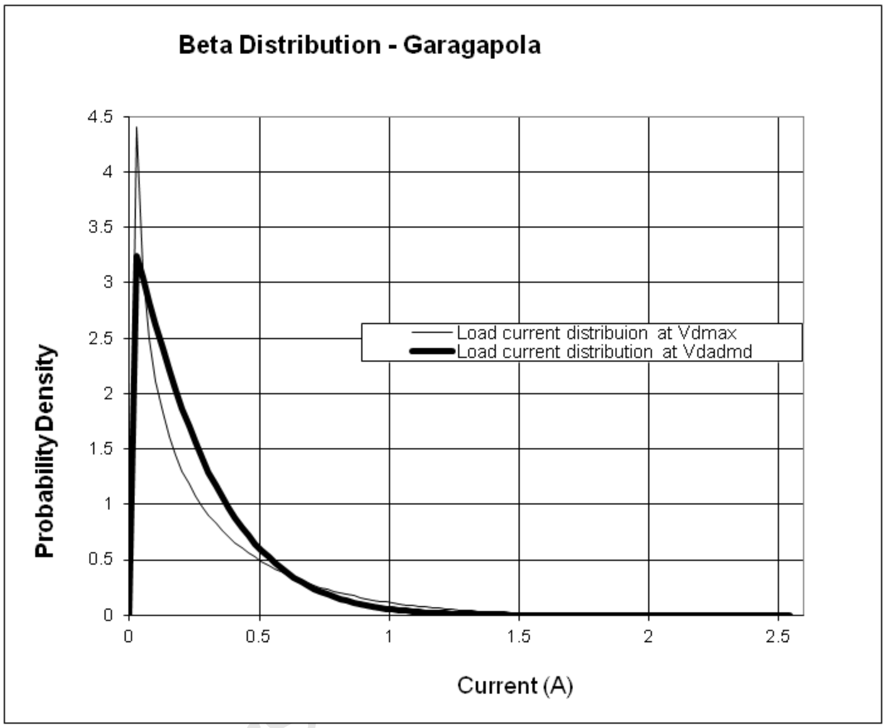


Figure 5.3: Beta pdf for α_{admd} and α_{Vdmax}, with α_{admd} and α_{Vdmax} not coincident

It is apparent from figures 5.2 and 5.3 that voltage drop magnitude is affected by both load magnitude and the degree of load current distribution. The load current distribution, representing variation in loads drawn by independent households, appears to play the more principal role. In other words, a load point at maximum load displaying low load current distribution will most likely experience a lower voltage drop compared to a point at a similar or relatively lower load magnitude with a higher degree of load current distribution. This explains why maximum voltage drop and maximum load sometimes do not always coincide. It must be emphasized however that load magnitude isnot negligible. .

5.2.1 Conclusions

ADMD-based load parameters have been presumed to be characteristic of residential loads. It was supposed that designs based on the loading conditions at the time of maximum demand (or ADMD) would not experience voltage drops outside QoS compatibility levels assuming 0% risk was used to calculated voltage drop. This is because ADMD based parameters were believed to represent the worst case of expected voltage drops. However, the analyses carried out in section 5.2 show that maximum voltage drop does not always coincide with maximum demand. It was found that voltage drop magnitude depends on both load and the degree of load current distribution. This means that a designer cannot accurately predict the performance of a network derived from ADMD based parameters because demand is not the sole factor contributing to voltage drop magnitude. Also, the time of maximum demand represents a single period instead of the entire 1 week period. Therefore it cannot strictly be described as characteristic of the community with respect to voltage quality compliane.

5.3 COMPARING THE TRADITIONAL ADMD BASED PARAMETERS TO THE NEW QoS BASED DESIGN PARAMETERS

NRS 034-1 [2007] brought forward the need to incorporate LV network voltage performance measurement techniques defined by NRS 048-2 [2006] into formulating a new set of design parameters. These new parameters are required to combine the load modelling techniques defined in NRS 034-1 with the voltage regulation specifications of NRS 048-2.

NRS 048-2 [2006] requires that 95% of voltages drops measured during a minimum assessment period of 1 week taken anytime during the year must be within the compatibility limits. This means that 5% of the measured voltage drops are allowed to be in violation.

Using the Beta pdf to model the loads, a set of new design parameters was derived based on the 95% compliance criterion of NRS 048-2 [2006]. For each community the Herman Beta method was used to calculate voltage drops for all 2016 load points for the worst week using 10 minute data. From these voltage drop values a load point was defined that allowed for 5% of the calculated voltage drops to exceed it. However, the Herman Beta method calculates voltage drop using statistical methods and therefore has an associated design risk. Increasing the design risk in this application increases the probability that the calculated voltage drop will be surpassed in the built network. For example, calculating voltage drop at 0% risk means there is a 0% probability that the calculated voltage drop value will be surpassed on the actual network, if the input parameters used for the calculations are reflective of the community load and the network connections. At 5% risk, there is a 5% chance the calculated voltage drop will be surpassed also assuming input parameters are reflective of the actual. Therefore, in order to derive QoS parameters that meet NRS 048-2's 95% compliance criterion, parameters calculated from low design risks were permitted to allow for more violations and higher risk designs were restricted to lower numbers of voltage violations in order to achieve 95% overall compliance. 3 combinations of risk-to-violations were used to derive the new QoS design parameters. The following combinations, each allowing 5% violation (95% compliance) were used:

1. 0.1% risk – 99 violations (Voltage drops for worst week calculated at 0.1% risk)
2. 2.5% risk – 52 violations (Voltage drops for worst week calculated at 2.5% risk)
3. 5% risk – 0 violations (Voltage drops for worst week calculated at 5% risk)

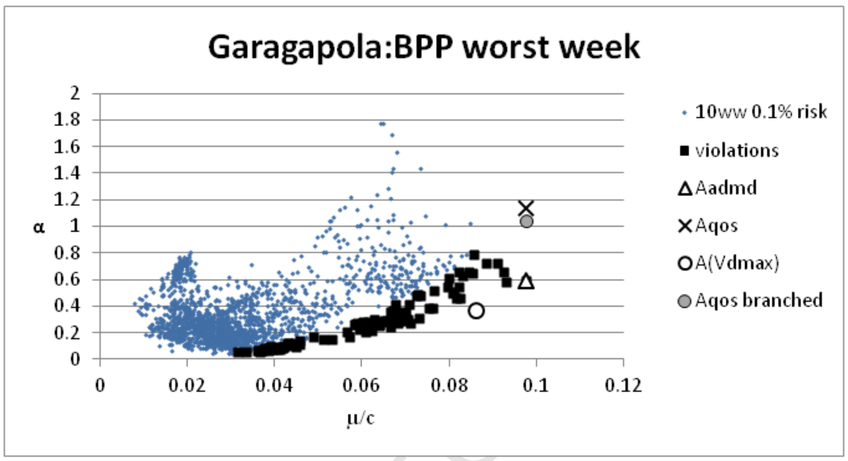
It is assumed that since all combinations allow for 95% compliance, they will generate a similar load point. The BPP will be used to display the 2016 load points of each community during the worst week. Along with α_{admd} and $\alpha_{Vdmax,}$ each plot will show the new QoS design points derived from the NRS 048-2's 95% compliance criterion. The QoS parameters will be depicted by the following load points:

α_{qos} - Beta parameter α for QoS design point for linear feeder topology

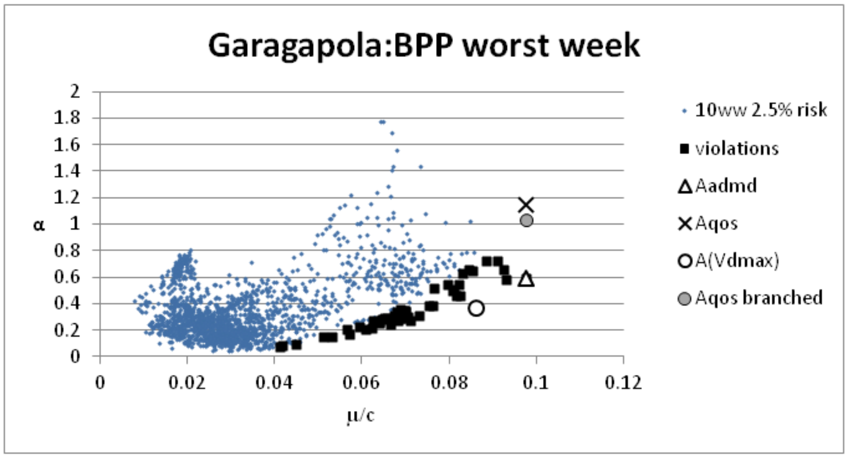
$\alpha_{qos\ (branched)}$ - Beta parameter α for QoS design point for branched feeder topology

α_{qos} points for both the linear and branched topologies were calculated at the maximum recorded load i.e. maximum μ/c for each community and therefore lie on the same line of μ/c as α_{admd}. This was done in order to relate the new parameters to the ADMD using COV curves which will be discussed in chapter 6.

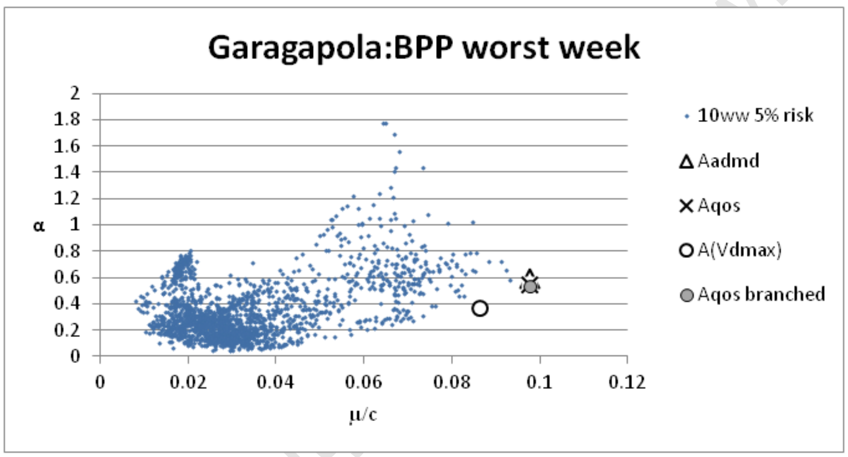
Figure 5.4 shows the BPPs of one of the measured communities. The rest are provided in appendix C.



(a) 0.1% risk – 99 violations



(b) 2.5% risk – 52 violations



(c) 5% risk – 0 violations

Figure 5.4: BPP for Low income community showing α_{qos}, $\alpha_{qos(branched)}$, α_{admd} and α_{Vdmax}.

The α_{qos} parameters for the branched and linear feeder arrangements are higher in value to α_{admd} for the 0.1% risk - 99 violations and 2.5% risk - 52 violations combinations. This means these α_{qos} parameters will produce lower voltage drops to those calculated at α_{admd} for these combinations. The lower voltage drops are a result of these risk-to-violation combinations allowing for voltage drop violations.

For 5% risk – 0 violations, α_{qos} produces calculated voltage drops equal to the maximum voltage drop expected by each community as it does not permit any voltage drop violations. Therefore if maximum demand and maximum voltage drop are not coincident, as is the case in figure 5.4,

α_{qos} leads to a higher voltage drops compared to α_{admd}. In the cases where the load point of maximum demand produces the highest voltage drop α_{qos} and α_{admd} are coincident.

Figure 5.5 shows the load current distributions at the time of maximum demand (α_{admd}) and figure 5.6 the load current distributions represented by the QoS design parameters for the middle income communities. The QoS parameters shown in figure 5.5 were calculated at 0.1% risk – 99 violations for the linear feeder arrangement.

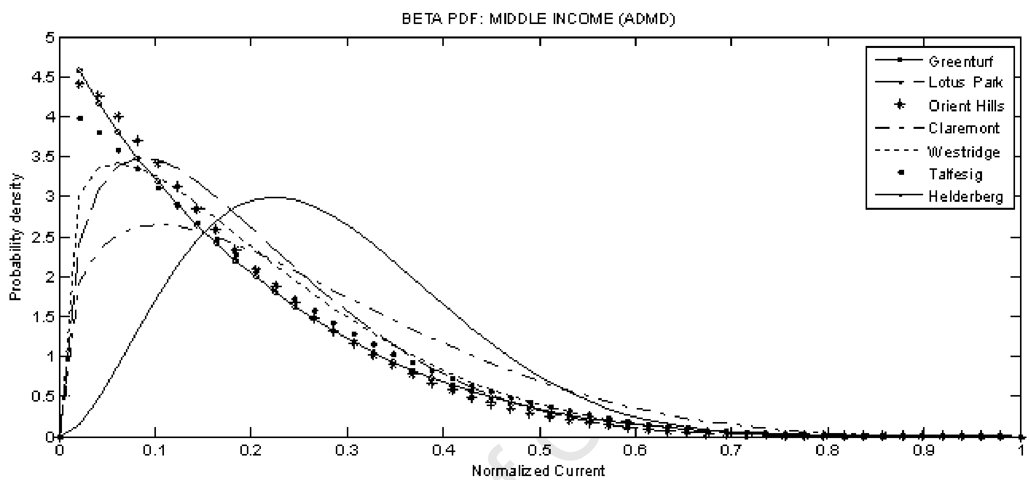


Figure 5.5: Beta pdf at α_{admd} for middle income communities, 0.1% risk

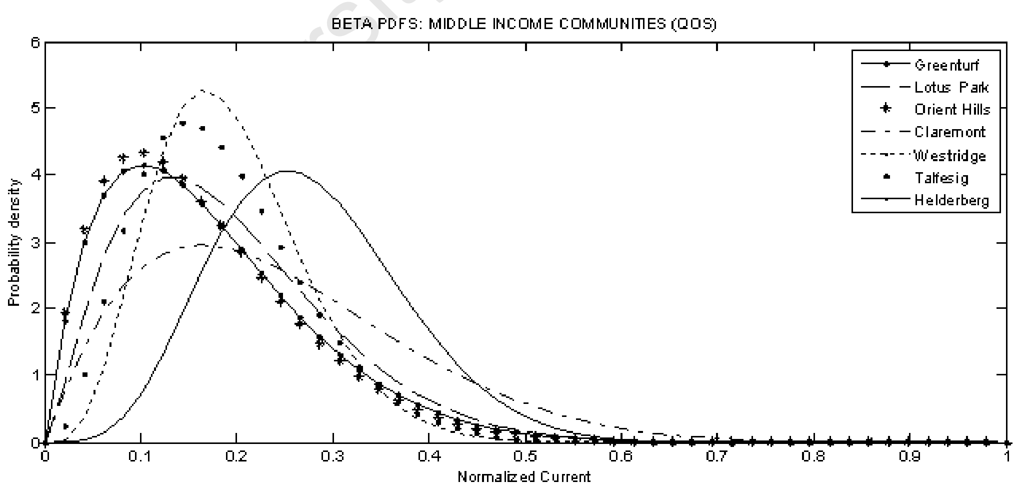
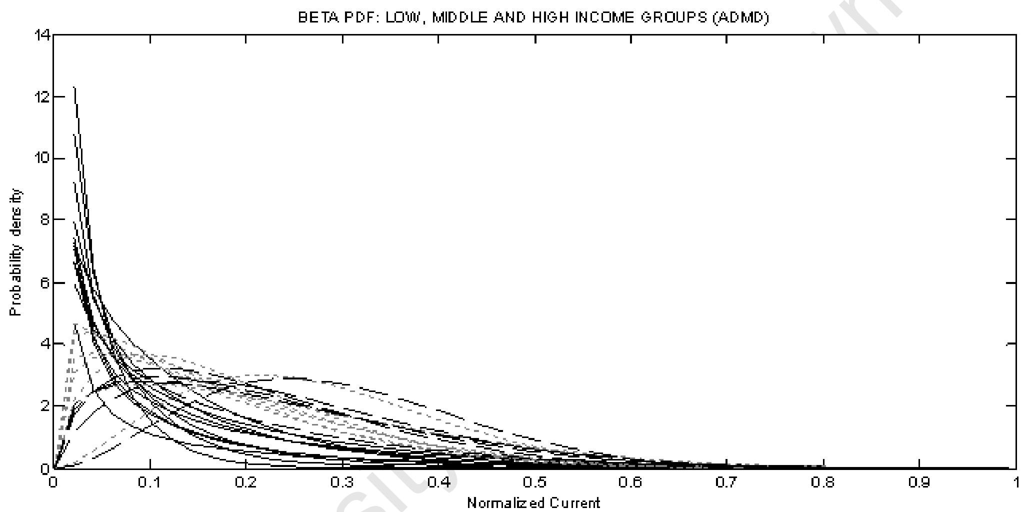


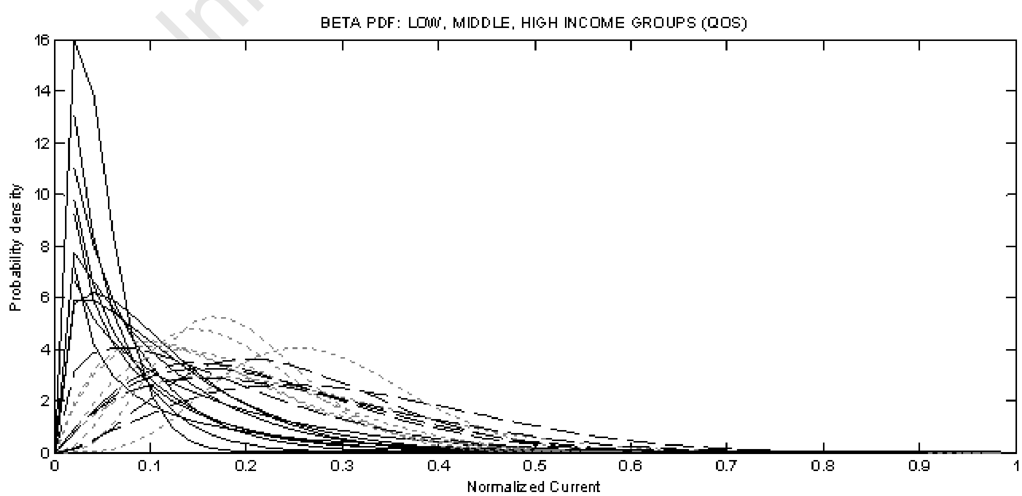
Figure 5.6: Beta pdfs at α_{qos} for middle income communities, 0.1% risk-99 violations

The load current distributions at the time of maximum demand represented by α_{admd} are more dispersed than the load current distributions represented by the α_{qos} parameters. This means α_{qos} parameters, with the exception of those derived from 5% risk – 0 violations, will lead to lower voltage drop estimates compared to calculations based on the α_{admd} parameters.

Figure 5.7 shows the load current distributions at α_{qos} and α_{admd} for all the measured communities. For all income groups, α_{qos} are expected to produce lower voltage drops in comparison to the α_{admd} design parameters derived from all risk-to-violation combinations except 5% risk – 0 violations.



(a) Beta pdfs at α_{admd} and β_{admd}



(b) Beta pdfs at α_{qos} and β_{qos} 0.1%-99 violations

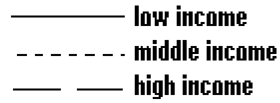


Figure 5.7: Beta pdf for the investigated low, middle and high income communities

5.3.1 Conclusions

- Unlike ADMD-based load parameters, a designer can estimate the number of violations expected on a LV network designed using the QoS load parameters. This expected number of voltage drop violations is 5%. These QoS parameters are however based on the worst week of the measured communities. They are likely to change when considering a different week to the worst week or using a longer assessment period.
- QoS design parameters are more characteristic of residential load as they consider the load conditions of the entire assessment period compared to ADMD-based parameters that just consider the time of maximum demand.
- The QoS design parameters are dependent on the risk-to-violation combination used to derive them. α_{qos} parameters derived from 0.1% risk – 99 violations, 2.5% risk – 52 violations and 5% risk – 0 violations are not equal as was expected. This is because the different risk-to-violation combinations allow for different numbers of violations. If 0 or an equal number of violations was permitted for all three combinations then the α_{qos} parameters would have been more likely to be coincident.
- α_{qos} parameters derived from 0.1% risk – 99 violations and 2.5% risk – 52 violations produce designs that are less conservative than α_{admd} based designs.
- The QoS design parameters are dependent on the feeder topology. This is evident because α_{qos} values for the branched feeder topology are not coincident with the α_{qos} values for the linear feeder arrangement. This will be discussed in section 5.6.

5.3.2 Further observations

Figure 5.7(a), displaying pdfs at α_{admd} and β_{admd} for the different communities, shows the high income communities have load current dispersions that are fairly similar to the middle income communities, which is not typically expected. This is because high income areas are more likely to have reached appliance saturation and as a result individual households tend to draw similar amounts of load currents.

A possible explanation as to why high income communities are showing load current distributions similar to middle income areas is the possible use of energy saving appliances or renewable energy supplies such as solar panels. This could explain the increased variation in load currents drawn in high income communities as not all households in the community will be utilizing these energy saving appliances and renewable resources. HWC penetration might also be a factor however there is not enough data on HWC penetration to base a reliable conclusion.

Another possibility is that the circuit breaker used for the middle income communities was low to the point that it limited electricity use, consequently leading to a more normalized pdf similar to that of the high income consumers. To check this theory, a stacked column bar graph, figure 5.8, was plotted to compare the average load for each community at a certain time to the corresponding scaling factor. The maximum load drawn by a single household was used as the scaling factor. The bottom bar of the stack represents the average load for the community whilst the top bar shows the maximum individual load i.e. the scaling factor. If a maximum appears at or close to the average load then it can be assumed that circuit breaker limiting influenced the load current distributions.

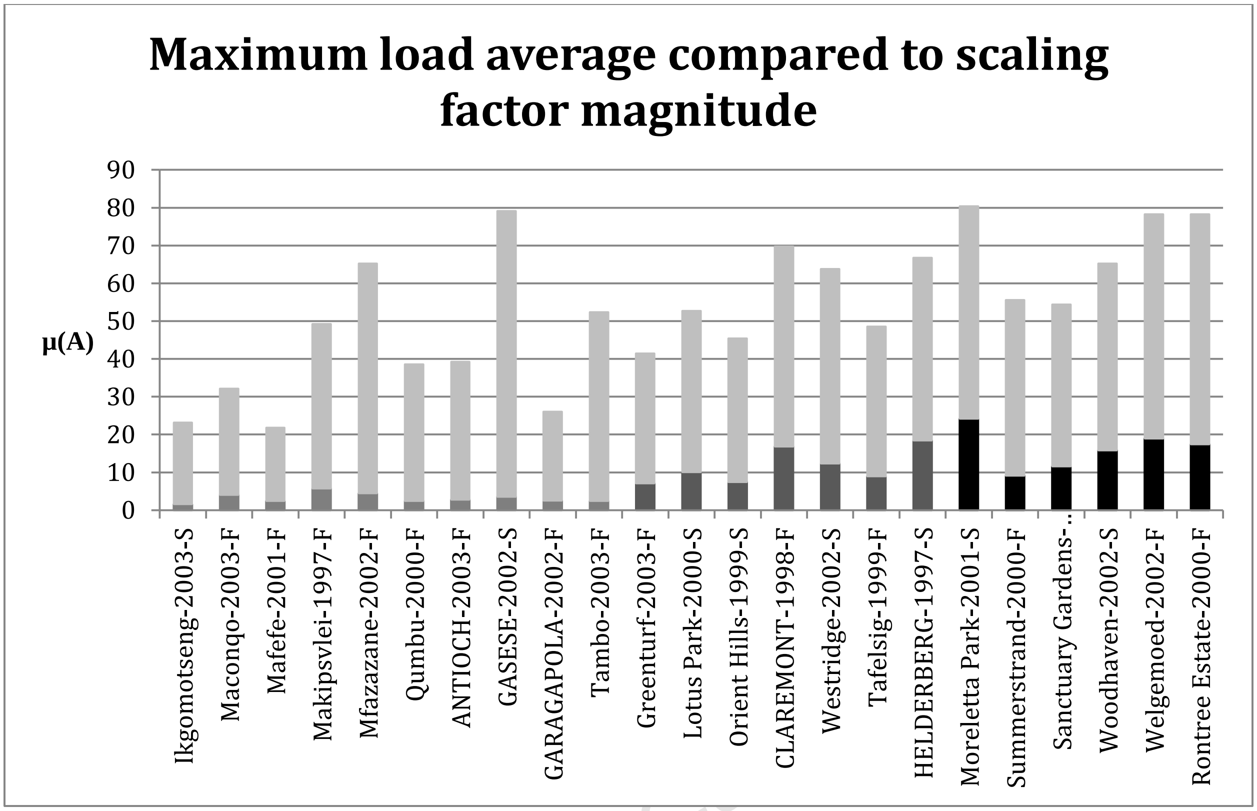


Figure 5.8: Load magnitude for low, middle and high income communities in relation to the scaling factor.

Figure 5.8 shows that the scaling factor and thus the actual circuit breakers used for the measured communities did not limit electricity use as there is significant difference between the average load current drawn by each community and its corresponding scaling factor. Therefore, the degrees of skewness depicted in figure 5.7 are reflections of uninhibited electricity use of the measured communities.

Figure 5.9 shows the relationship of voltage drops between the different income classes calculated using QoS parameters. Because of lower load dispersions, the middle income communities are expected to create lower voltage drops along the feeders compared to the high income communities. The low income communities are expected to produce the lowest voltage drops and therefore the cheapest designs because of the low magnitudes of load drawn in this class of consumers.

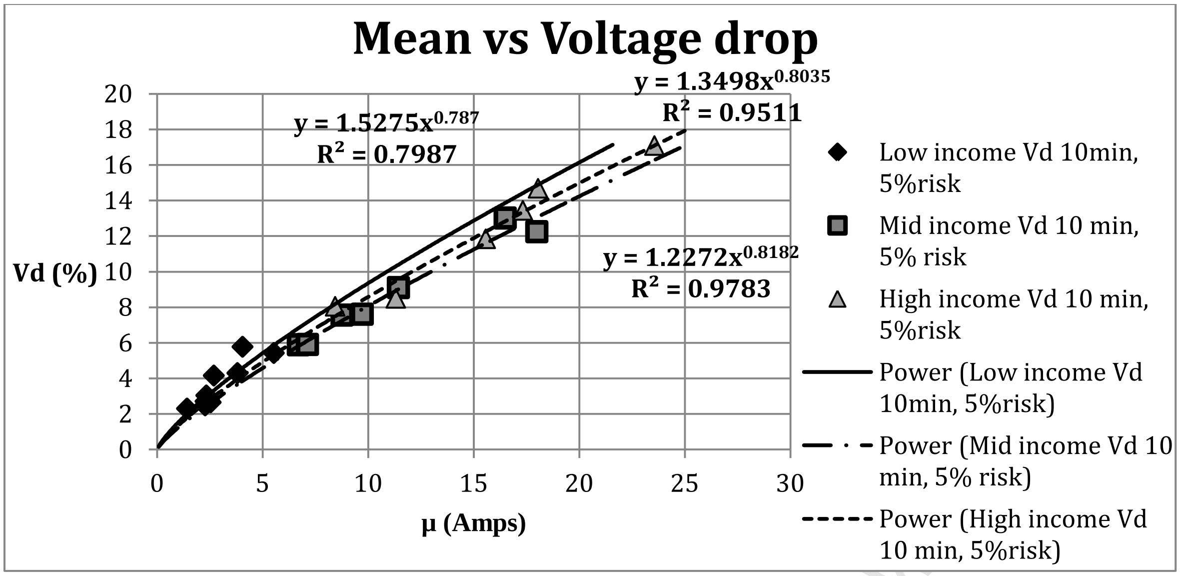


Figure 5.9: Voltage drop magnitude derived from calculated α_{qos} for low, middle and high income groups, 5% risk

5.4 EXPECTED VOLTAGE DROP CALCULATED FROM QoS PARAMETERS DERIVED FOR DIFFERENT RISK-TO-VIOLATION COMBINATIONS

In section 5.3 it was found that QoS parameters were dependent on the risk-to-violation combination used to derive them. The 3 combinations of risk-to-violations were used to derive α_{qos} parameters. All 3 combinations should lead to 95% voltage drop compliance. This section investigates the implications of each risk-to-violation combination on the expected voltage drops along a feeder.

The voltage drops expected along the feeders were calculated using the Herman-Beta method. All parameters of the Herman-beta spreadsheet, except α=αqos, β=βqos and c=maximum measured household load, that are specific to the community being investigated, were kept constant so the results would be comparable. The results are shown in figures 5.10-5.12.

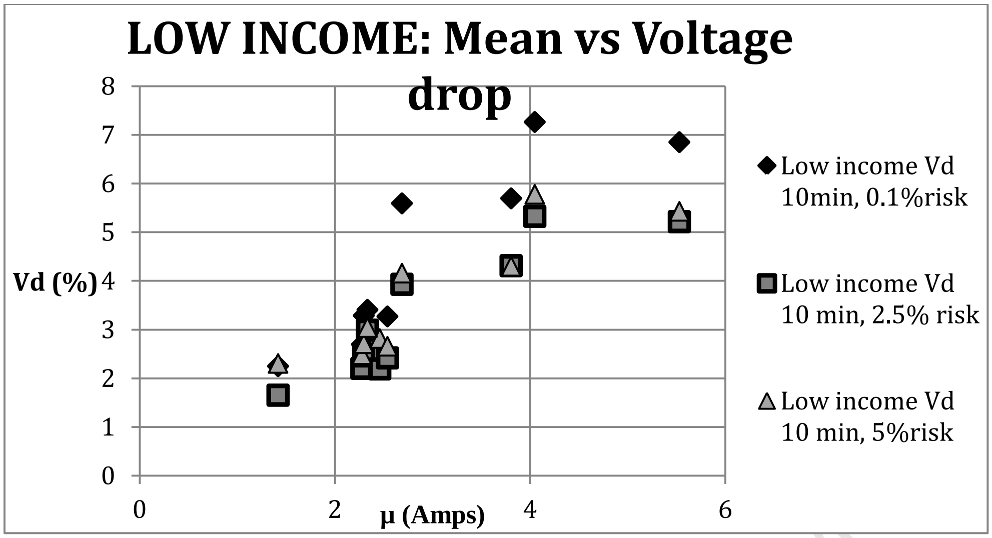


Figure 5.10: Voltage drop magnitude for low income communities at different risk-to-violation combinations

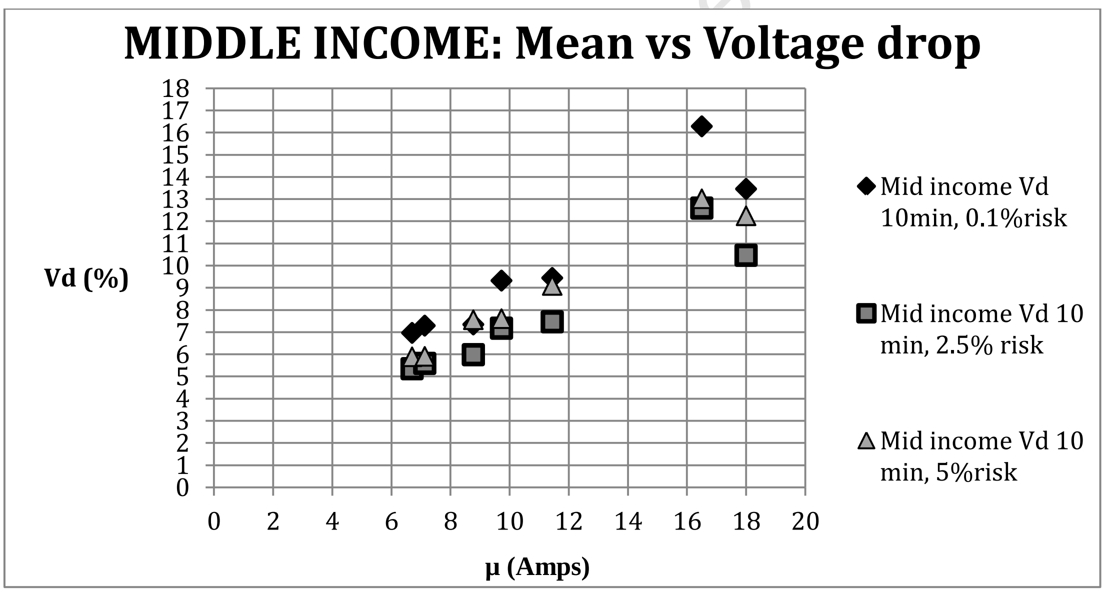


Figure 5.11: Voltage drop magnitude for middle income communities at different risk-to-violation combinations

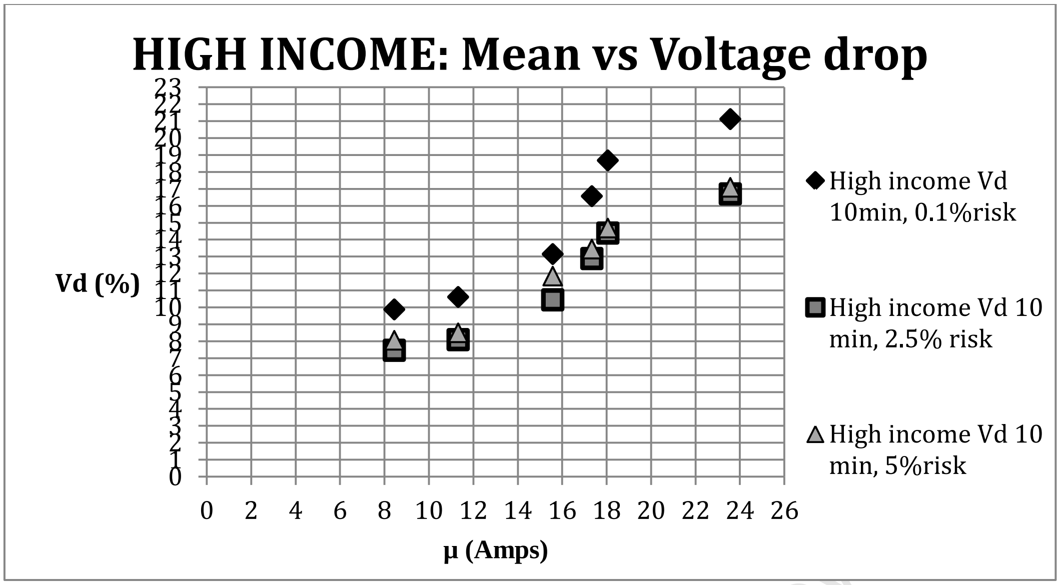


Figure 5.12: Voltage drop magnitude for high income communities at different risk-to-violation combinations

For all instances:

- 0.1% risk, 99 violations produced the highest voltage drops
- 2.5% risk, 52 violations produced the lowest voltage drops

Voltage drops for 0.1% risk - 99violations, 2.5% risk - 52violations and 5% risk -0 violations were calculated at 0.1% risk, 2.5% risk and 5% risk respectively. Although calculated from same 2016 pairs of α and β for the worst week, voltage drops calculated at 0.1% risk will be the highest and those calculated at 5% risk the lowest. If all QoS design parameters were restricted to 0 violations then all the design parameter would represent maximum voltage drop which will be highest when calculated at 0.1% risk and lowest at 5% risk. However, because violations are permitted for 0.1% and 2.5% risk voltage drops lower than their respective maximums are used, leading to the results produced in figures 6.10-6.12.

5.5 EXPECTED VOLTAGE DROPS RELATIONSHIPS OF QoS PARAMETERS BASED ON DATA AVERAGED OVER 5, 10 AND 20 MINUTES

NRS 048-2 requires that data averaged over a 10 minute period be used to assess QoS compliance of a network. This section investigates how the length of the period data is averaged effects the voltage drop magnitudes calculated using QoS parameters derived from load data averaged over different periods. Load data averaged over 5-, 10- and 20 minute periods was used to derive QoS parameters. Figures 6.13-6.15 show that 5 minute data results in the highest voltage drops, followed by 10 minute then 20 minute averaged data samples. This is a result of the household load magnitudes decreasing as the averaging time increases. Therefore averaging bares significance on the efficiency of a design. A design runs a higher risk of being under-designed if it is based on a low resolution data.

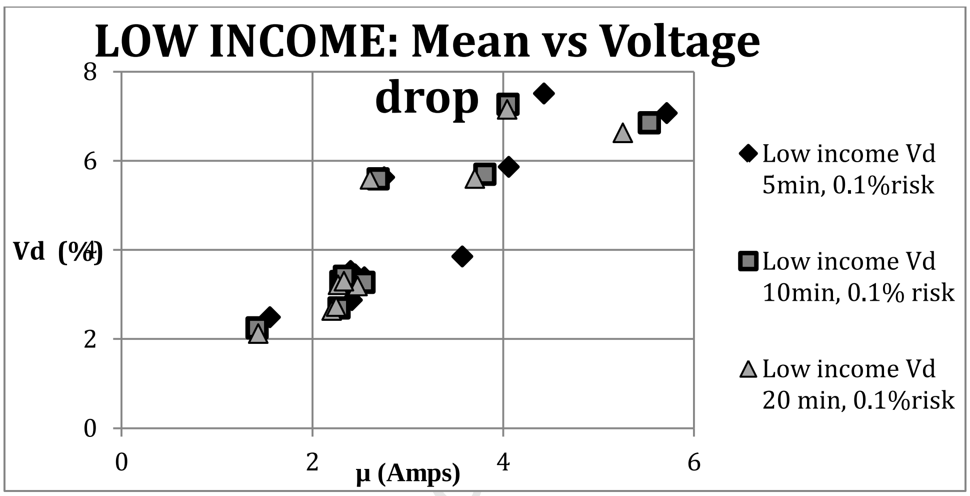


Figure 5.13: Voltage drop magnitude for low income communities at different average times

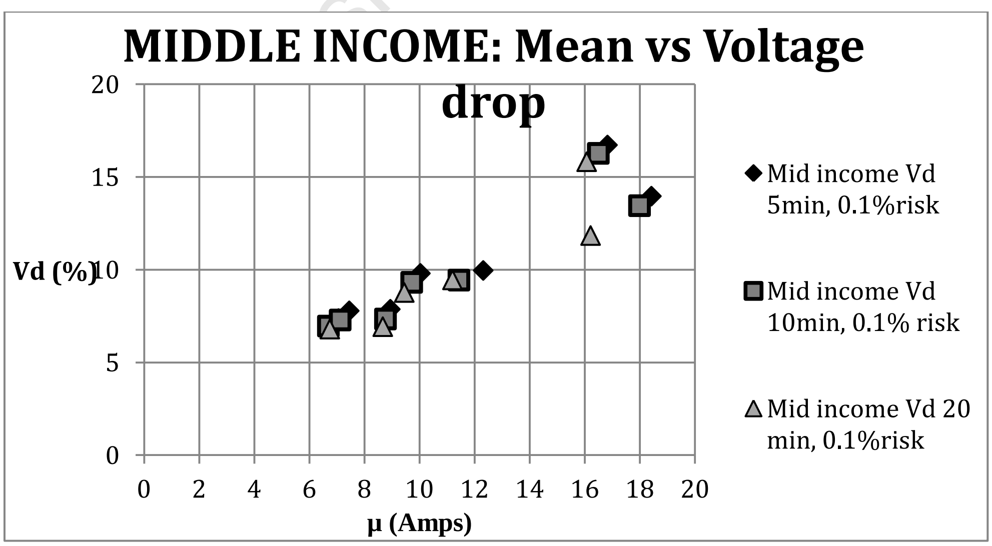


Figure 5.14: Voltage drop magnitude for middle income communities at different average times

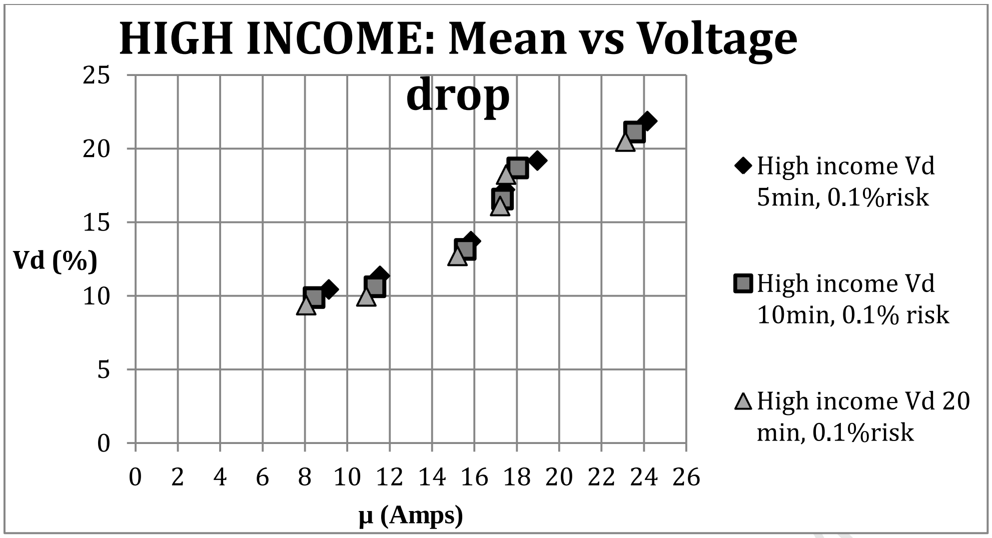


Figure 5.15: Voltage drop magnitude for High income communities at different average times

5.6 COMPARING THE NEW α_{qos} PARAMETERS FOR LINEAR AND ASYMMETRICALLY BRANCHED FEEDER TOPOLOGIES

In section 6.3 it was found that feeder topology influences the QoS parameters derived. Network designers have the freedom to select the topology of the feeders. The effects of different topologies on the QoS design parameters and consequently the voltage drop predictions was investigated by comparing voltage drops calculated from a linear and asymmetrically branched feeder layouts. Figure 5.16 shows the results.

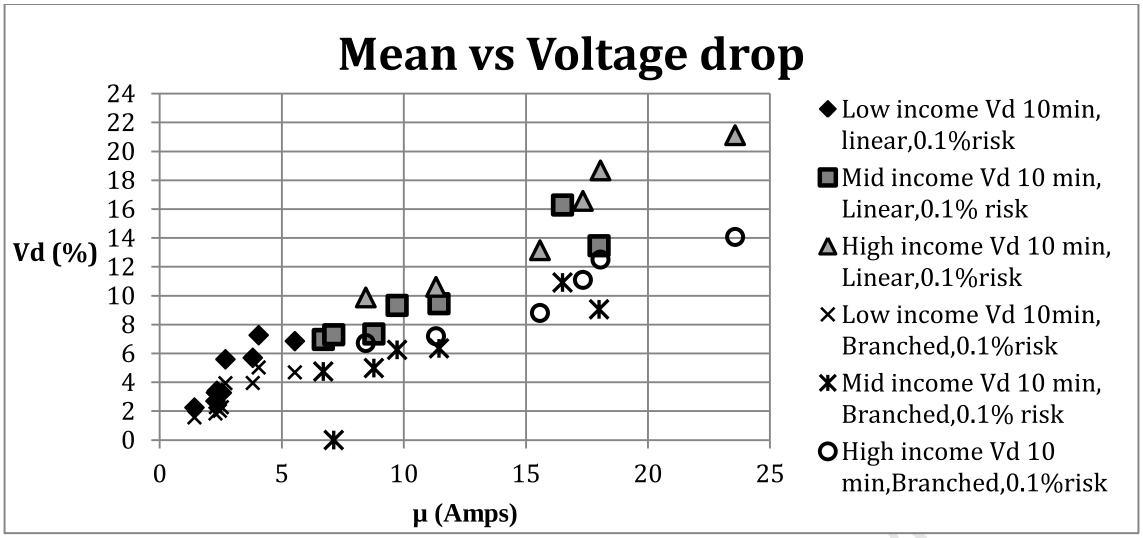


Figure 5.16: Voltage drop measure for branched and linear arrangement for different income groups at 0.1% risk

The voltage drops were calculated at 0.1% risk and the QoS parameters were derived using the 0.1% risk - 99violations combination. In all cases the voltage drop magnitudes for the branched network is always lower than that of the linear network for each income group. This can be explained by the fact that customer loads are more evenly distributed in a branched network.

5.7 CONCLUSIONS ON QoS PARAMETERS

- QoS parameters are affected by several factors which include:
    a. The time and length of the assessment period
    b. Feeder topology
    c. Averaging time of load data
    d. The risk –to-violations combination from which they are derived, and
    e. Load class
- From the QoS parameters, high income communities are expected to experience the highest expected voltage drops and low income communities are expected to experience the lowest voltage drops.
- Designs based on QoS parameters derived from 0.1% risk - 99 violations and 2.5% risk - 52 violations are less conservative compared to designs based on maximum demand parameters, as they allow for voltage drop violations.

- Although all QoS parameters allow for 95% compliance 0.1% risk - 99 violation QoS parameters are expected to produce the most conservative designs out of all the QoS design parameters derived from the 3 risk-to-violation combinations. 2.5% risk - 52 violation QoS parameters are expected to produce the least conservative designs. This is based on the condition that the voltage drops are calculated at the associated risks of the risk-to-violation combinations. Therefore the set of QoS parameters used is significant as it affects the expected voltage drops of the feeder network being modelled.
- Branched feeder arrangements were found to produce lower voltage drops compared to the linear topologies. This is due to the fact the load is more evenly distributed in branched feeders thus resulting in lower voltage drops expected to be experienced along the feeders.
- Increasing the period data is averaged decreases the magnitude of the calculated voltage drop. Data resolution is therefore significant as low data resolution can lead to design parameters that underestimate the expected voltage drop, increasing the probability of future network upgrading.
- Overall, QoS parameters are more representative of residential load as they take into account loading conditions during the entire assessment period compared to ADMD based parameters which only consider the single instance of maximum demand.

6

DERIVING QOS DESIGN PARAMETERS FOR PLANNING AND DESIGN

The Coefficient of Variation (COV) curve was introduced in [Herman and Gaunt, 2008] and has been discussed in section 2.2.4. Herman and Gaunt [2008] found a strong relationship between the ADMD and the coefficient of variation (γ) of the current design parameters for the LSM customer classes defined in NRS 034-1. This relationship was modelled as $\gamma = 1.1427d^{-0.412}$ *where d is the demand in kVA.*

The load parameters of the LSM customer classes used to develop the COV curve shown in figure 2.13 by Herman and Gaunt represent the maximum demands expected for each load class. This chapter aims to develop a COV curve similar to that of Herman and Gaunt but using the newly derived QoS load parameters instead. If a suitable COV curve is obtained, designers can use the expected ADMD of a community to obtain appropriate QoS design parameters to base their designs. The suitability of a COV curve will be determined by assessing the Goodness of Fit.

6.1 INTRODUCTION

The COV curve is based on the relationship between γ (coefficient of variation) and μ (ADMD) given by equation 6.1.

$\gamma = \sigma/\mu$ ...Equation 6.1

where:

$\sigma = \sqrt{\frac{c^2\alpha\beta}{(\alpha+\beta^2)(\alpha+\beta+1)}}$ ...Equation 6.2

and

$\mu = \frac{c\alpha}{(\alpha+\beta)}$ ...Equation 6.3

The purpose of the COV curve in this case is to relate the ADMD of the measured communities to the newly derived QoS parameters. Thus Equation 6.1 is rewritten as Equation 6.4.

$\gamma_{qos} = \sigma_{qos}/\mu$ ...Equation 6.4

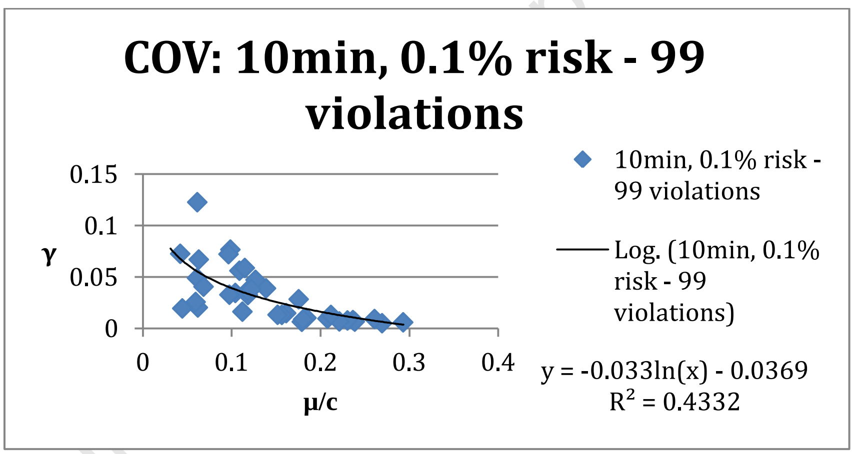
where

μ is the ADMD in Amps (A)

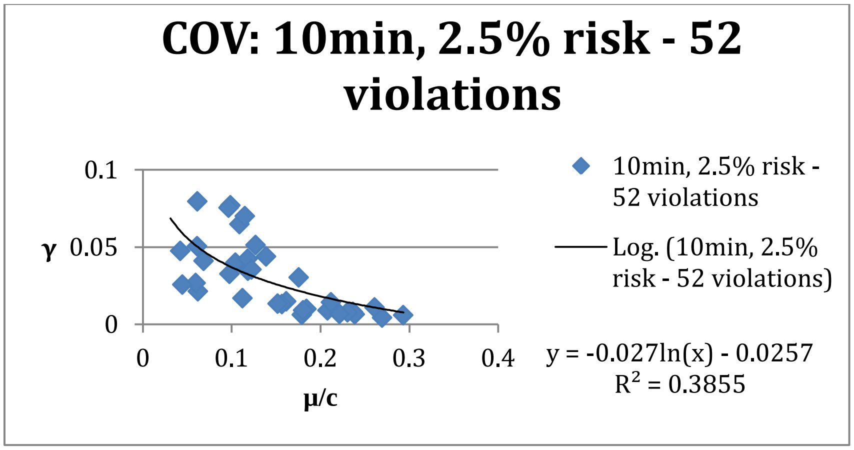
and

σ_{qos} is the standard deviation of the QoS design parameters.

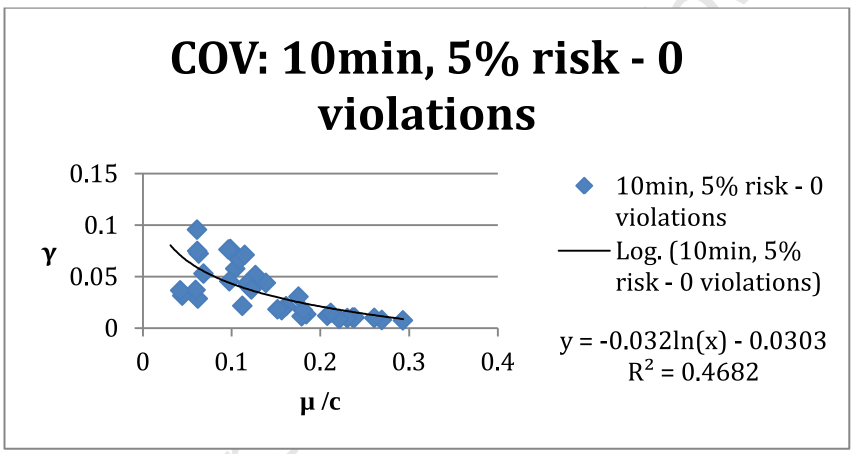
QoS design points derived from the different risk-to-violation combinations for all measured communities were plotted on a γ against μ/c plot. Equation 6.4 was used to calculate the γ_{qos} values of the QoS parameters. μ represented the highest measured average load for each community and c was taken to be the highest measured load current drawn by a single household for each community. Designers can take c to be the load limiting circuit breaker rating in Amps and μ to be the ADMD in Amps.



(a) COV curve for QoS design parameters calculated at 0.1% risk – 99 violations



(b) COV curve for QoS design parameters calculated at 2.5% risk – 52 violations

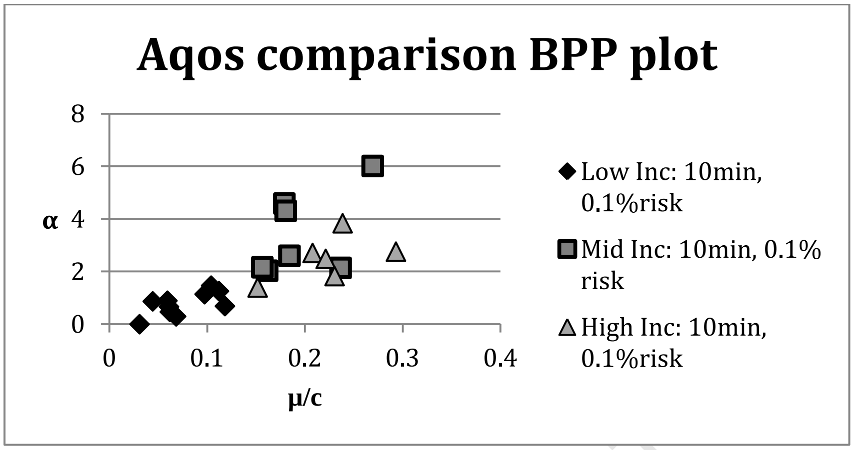


(c) COV curve for QoS design parameters calculated at 5% risk – 0 violations

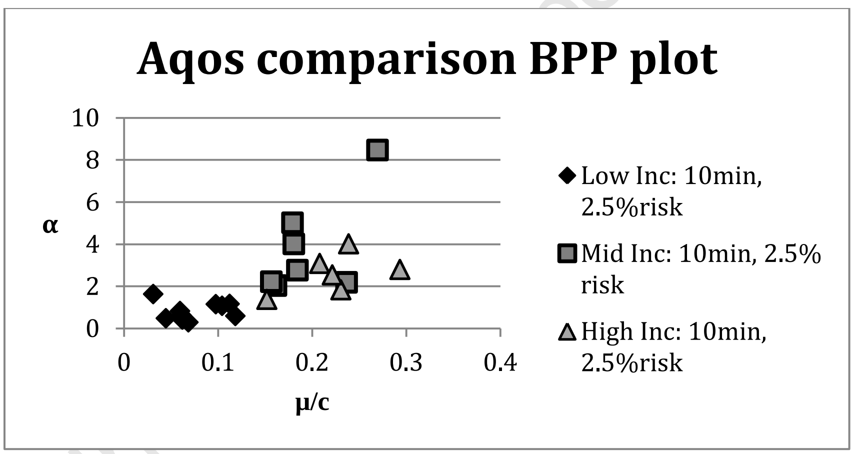
Figure 6.1: A COV curve for QoS design points, derived at different risk-to-violation combinations, for low, middle and high income communities. Using 10 minute averaged data

Figure 6.1 shows the COV curves trending the relationship between the QoS design points derived using the 3 risk-to-violation combinations. The 5% risk – 0 violation QoS design parameters showed a higher degree of correlation of 0.4682 compared to the QoS design parameters produced from the 0.1% risk – 99 violations and 2.5% risk -52 violations which showed correlations of 0.4332 and 0.3855 respectively.

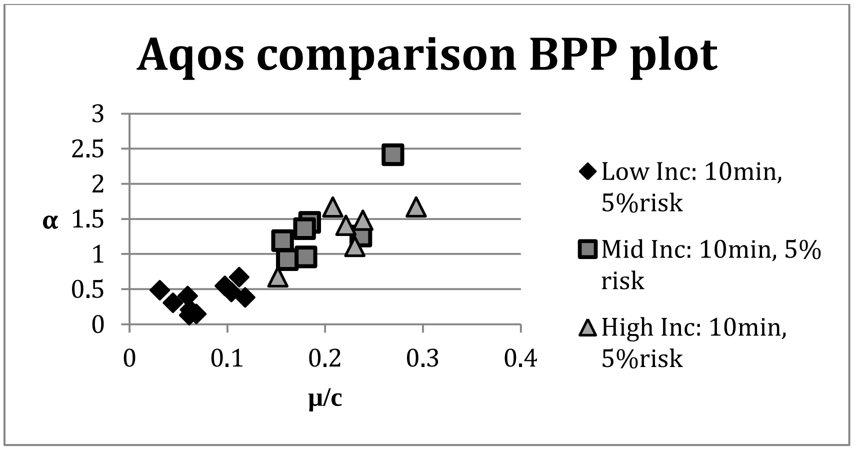
Figure 6.2 shows the QoS parameters derived from the different risk-violation combinations on BPPs. The QoS points for 2.5% risk – 52 violations show the highest degree of scatter and those for 5.0% risk – 0 violations show the least scatter. Correspondingly the 5.0% risk – 0 violations COV curve shows the highest correlations and the 2.5% risk – 52 violations COV curve shows the lowest correlations.



(a) QoS parameters calculated for 0.1% risk – 99 violations



(b) QoS parameters calculated for 2.5% risk – 52 violations



(c) QoS parameters calculated for 5.0% risk – 0 violations

Figure 6.2: BPP of αqos points for low, middle and high income communities for different risk-violation combinations

Ideally correlation levels closest to of $R^2 = 1$ are preferred. All three sets of QoS design parameters showed correlation of $R^2 < 0.47$ which are too low. In an attempt to achieve higher correlations different criteria of load classification were used. These criteria were:

1. Income group classification
2. Geyser penetration classification
3. Demand classification

Each class should preferably have its own representative COV curve. The results of classification methods are provided in the following sections.

6.2 COV CURVES USING INCOME CLASSIFICATION

From figure 6.1 (a), (b) and(c) it is evident that the weak correlations of QoS parameters on the COV plots is subject to the increase in the scatter of points occurring at the lower μ/c values. A low μ/c is typically representative of the lower income communities. Also, upon inspection of figure 6.1 the points that appear to drift off from the rest causing a reduction in correlation were found to be the points with COV values of $\gamma \geq 1.5$. High COV values characterize a high degree of load current distributions. As was shown in chapter 6, low income communities show the highest degree of load current distributions.

Based on these observations, the QoS parameters were segregated by income class and the results provided in table 6.1 were achieved.

Table 6.1: Correlation of QoS design points for low, middle and high income communities.

Class	0.1% risk	2.5% risk	5% risk
Low income	0.1703	0.0865	0.0261
Middle income	0.5805	0.4238	0.724
High income	0.4465(E1)	0.3985(E2)	0.4955(E3)

6.2.1 Conclusions

The strength of QoS design parameter correlations on the COV curve is dependent on the load current distributions in communities constituting the load class. Figure 5.7(b) shows that based on the QoS parameters, the middle income group showed the lowest degree of load current distribution and the low income communities showed the highest degree of load current distribution. This explains why table 6.1 shows higher correlations for QoS design parameters for the middle income group and the lowest correlations for the low income communities.

COV curves for the middle income communities showed an improvement in R^2 values compared to the previous COV curves in section 6.1 were load classification was not used. QoS parameters for the low and high income communities showed weak correlations. Overall COV curves for the low, middle and high income communities are not good enough to recommend for use.

6.3 COV CURVES USING GEYSER USE CLASSIFICATION

Knowing the appliance penetration levels is important as it allows for more refined classification beyond just low, middle and high income. The current load data only holds information pertaining to geyser use, but the level of penetration in each measured community is not specified. Only 0% Geyser use was well defined. Therefore, for communities within which geysers were used, the degree of geyser penetration could not be considered.

The design points for all the communities were separated into 2 groups which were 1) No geysers and 2) with geysers. Since geysers have been found to be major load contributors due to the high amounts of power they draw, separating communities based on the presence of HWCs might achieve more significant relationships between points compared to those produced by separation based on income. Table 6.2 shows the resulting correlations based on geyser use classification.The corresponding COV curves are provided in appendix E to illustrate the results.

Table 6.2: Correlation of QoS design points for communities WITH geysers and with 0% Geysers

Class	0.1% risk	2.5% risk	5% risk
With Geysers	0.6456(E1)	0.611(E2)	0.7174(E3)
No Geysers	N/A (Figure 6.3)	N/A (E4)	N/A (E5)

Communities WITH geysers showed higher levels of correlations to those achieved by classifying based on income. The levels of correlation are still not high enough to recommend the COV for use. Communities with no geysers showed high levels of scatter which could not be trended as is shown by figure 6.3. Unfortunately information pertaining to the owned appliances, except HWCs, and the penetration of appliances for the communities in figure 6.3 is not available. This makes it impossible to further classify these customers based on appliances usage as was done by Dickert and Schegner (table 4.6) to hopefully achieve stronger correlations.

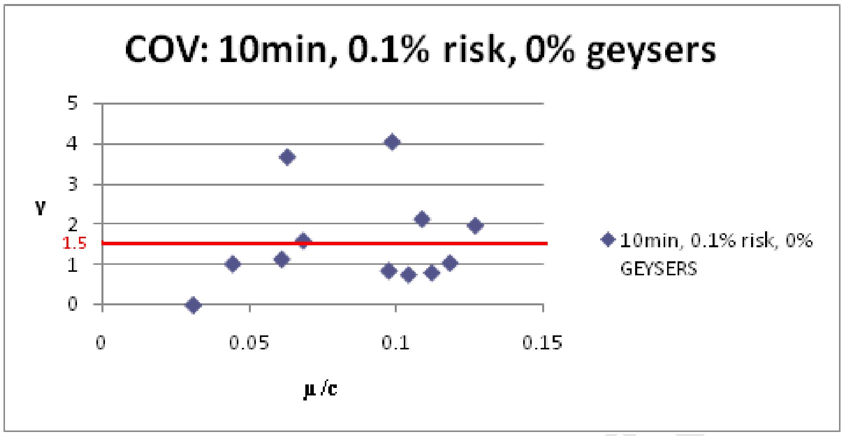


Figure 6.3: QoS design points derived at 0.1% risk, 99 violations, for communities with 0% geysers.

6.4 COV CURVES CLASSIFICATION BASED ON μ/c AND γ

A method that can be applied using the available data is separating points falling within the area $\gamma \geq 1.5$ and $\mu/c \leq 0.14$ which are displaying high levels of scatter. Table 6.3 gives the correlations achieved.

Table 6.3: Correlation of QoS design points for communities separated into γ<1.5 and γ≥1.5 groups

Class	0.1% risk	2.5% risk	5% risk
γ <1.5	0.756(figure 6.4)	0.7253(figure 6.5)	0.9152(figure 6.6)
γ ≥1.5	N/A (E6)	N/A (E7)	N/A (E8)

Although points defined by γ≥1.5 showed negligible correlations, those defined by γ<1.5 gave the highest correlations out of all the classification methods applied. The COV curves for γ<1.5 points are given in figures 6.4-6.6.

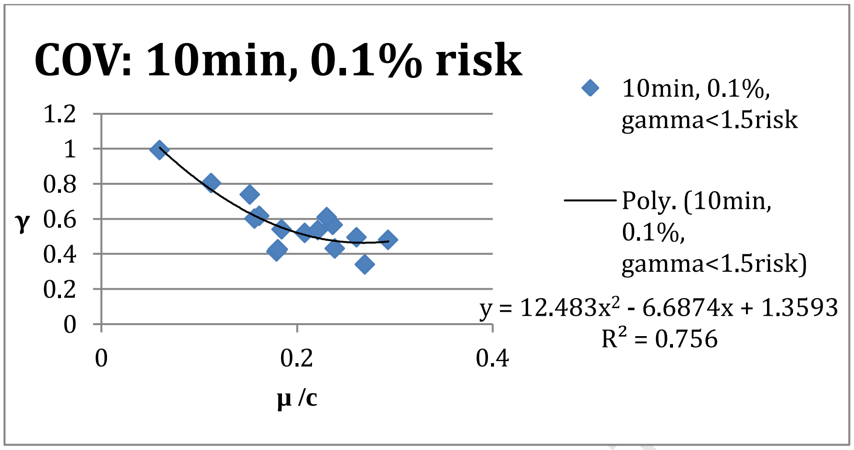


Figure 6.4: COV curve for γ<1.5 QoS design points, 10 minute data, 0.1% risk, 99violations

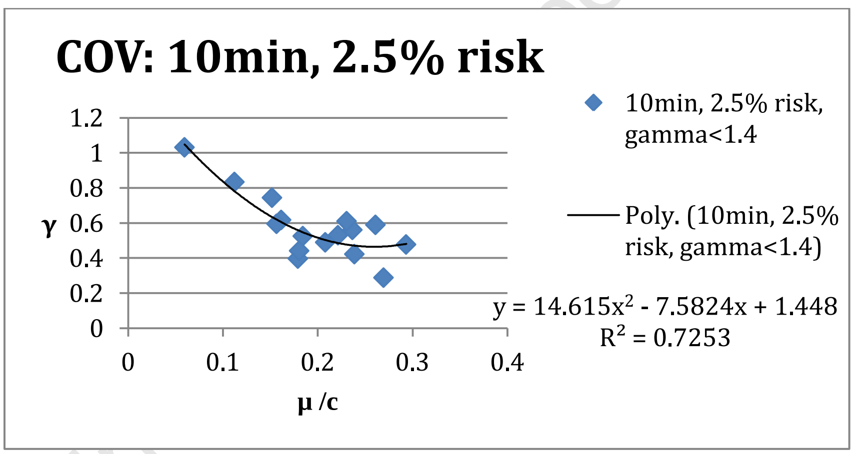


Figure 6.5: COV curve for γ<1.5 QoS design points, 10 minute data, 2.5% risk,52 violations

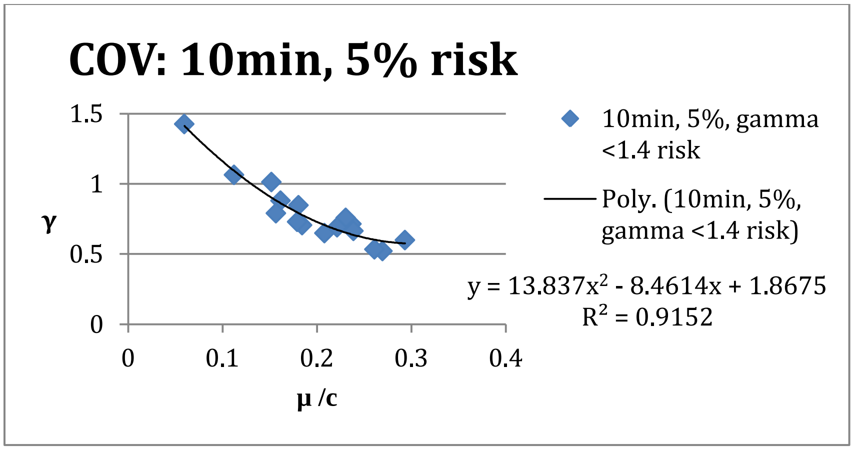


Figure 6.6: COV curve for γ<1.5 QoS design points, 10 minute data, 5.0% risk, 0 violations

The segregation of design points based on γ values could prove valuable if the γ ≥1.5 points, currently showing insignificant correlation, produce voltage drops below that achieved using the COV curves derived from the points with γ <1.5. If so, only the γ <1.5 COV curve could be used to model LV networks and the lack of correlation between the γ ≥1.5 points can be overlooked for now until more data is available to attempt further classification.

To test this, the COV curves of figures 6.4, 6.5 and 6.6 where mapped onto a BPP as shown in figures 6.7, 6.8 and 6.9 respectively. On each BPP the points of γ<1.5 from which each respective COV curve was derived were plotted to evaluate the performance of the curves since they did not produce perfect correlations i.e. $R^2 = 1$. The γ ≥1.5 points were also plotted on the BPPs. The distance of the points below the curve relates to the degree of voltage violation each point will incur with respect to the voltage drop expected on the curve at the same μ/c value [Gaunt, 1999].

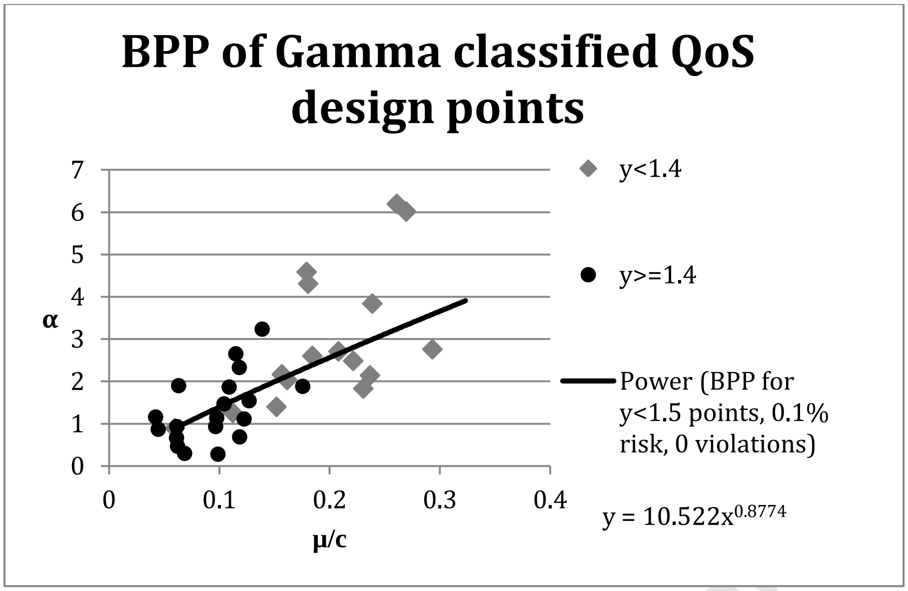


Figure 6.7: BPP with γ≥1.5 and γ<1.5 QoS design points, 10 minute data, 0.1% risk

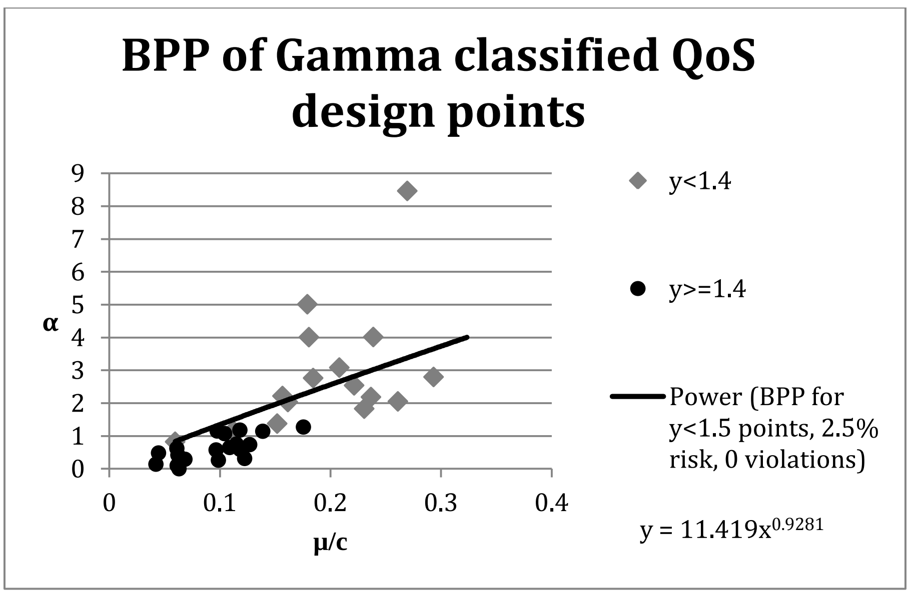


Figure 6.8: BPP with γ≥1.5 and γ<1.5 QoS design points, 10 minute data, 2.5% risk

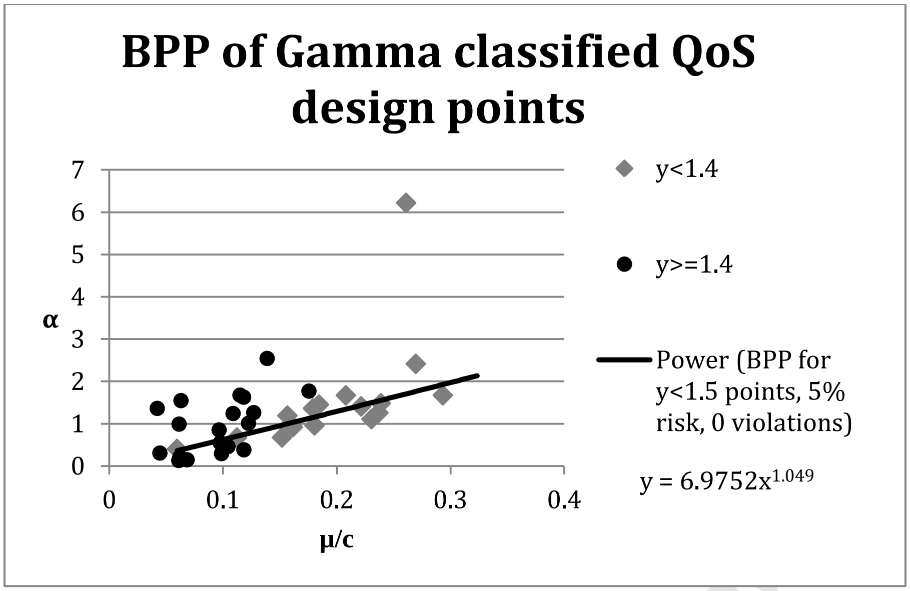


Figure 6.9: BPP with γ≥1.5 and γ<1.5 QoS design points, 10 minute data, 5% risk

From figure 6.9 it can be seen that majority of the γ<1.5 and γ≥1.5 are expected to produce voltage drops less than those from designs based on the BPP curve or respectively the 5% risk-0 violations COV curve. The γ<1.5 and γ≥1.5 expected to produce voltage violations, i.e. those occurring below the curve for the 5%-0 violations combination are likely to produce lower magnitudes of voltage drop violations compared to those of 0.1% risk- 99 violations (figure 6.8) and 2.5% risk - 52 violations (figure 6.7) as they do not stray too far from the BPP curve.

6.5 CONCLUSIONS

Different classification techniques affect the performance of the COV curve. Classifying load by income class gives week correlations for the low and high income groups whose QoS parameters show higher degrees of load current distribution. When classification based on geyser penetrations gave high correlations for QoS parameters for communities with geysers but no correlations were found for the communities without geysers.

The highest correlations were achieved for all risk-to-violation combinations when points were categorised as γ<1.5 and γ≥1.5. γ≥1.5 points showed negligible correlations. Using Beta parameter plots, it was found that the QoS parameters 5% risk-0 violations combination would produce designs less likely to experience voltage drop violations out of all the 3 combinations.

Also, the COV curve $\gamma = 13.837\left(\frac{\mu}{c}\right)^2 - 8.4614\left(\frac{\mu}{c}\right) + 1.8675$ for 5% risk-0 violations is suitable to derive design parameters for any type of community as can be seen from its performance on the BPP (figure 6.9). COV curves for 0.1% risk -99 violations and 2.5% risk - 52 violations QoS parameters are less likely to reliably predict the voltage conditions, particularly for the lower income communities.

7

CONCLUSIONS AND RECOMMENDATIONS

This thesis set out toincorporate QoS specifications into design parameters in order to build economic and reliable LV reticulation networks less prone to QoS violation. This chapter discusses the outcomes.

7.1 RESEARCH OUTCOMES – LV DISTRIBUTION NETWORK DESIGN

Voltage calculations are done at the design stage of LV networks in order to predict the performance of the proposed design. Current LV design parameters have been purposed to restrict the voltage supplied to customers from falling out of the compatibility limits set by QoS standards. These design parameters have traditionally been represented by the community ADMD or the statistical parameters of the load at the time of maximum demand. Previous research has found the ADMD to not be representative of load behaviour because it is a singular value representing the average maximum load. Statistical load models have been found to be more suited to modelling the stochastic nature of load. The Beta pdf was established as the probability distribution function that best mimicked load behaviour.

In South Africa, a set of Beta parameters α and β were derived to represent the statistical load conditions at the time of maximum demand for different consumer classes. These parameters have been used to design various LV networks while using the Herman Beta method to calculate the expected voltage drops. The reason for using load parameters representing the load at maximum demand is that it has been assumed that maximum voltage drop is experienced along a feeder at the time of maximum demand. Therefore it was believed that basing designs on the maximum loading conditions would reduce the likelihood of the voltage drop surpassing the compatibility limits imposed by QoS standards.

This research found that voltage drop magnitude is a factor of not only the load magnitude but the load current distribution as well. Therefore maximum voltage drop is not restricted to occurring at the time of maximum demand. As a result, a designer cannot assume to be designing for the worst case, in terms of voltage drop, when using maximum load parameters.

The NRS 048-2 QoS standard of South Africa permits 5% of voltage drops appearing on a feeder to be outside compliance limits. This means that voltage drop along the feeders should be within the compatibility limits 95% of the time. It has been found however that LV networks built from designs derived using design parameters based on the maximum demand have been prone to violating this 95% compliance criterion [Herman and Gaunt, 2011]. This investigation found that this tendency of current design falling short of the 95% compliance limit is mainly a consequence of calculating voltage drop at 10% design risk. This is the default design risk used to calculate voltage drop. Using 10% risk to calculate voltage drop means there is a likelihood of 10% that the voltage drop calculated will be exceeded. This means there is a likelihood of 90% that voltage drop will fall within the compatibility limits which is not compliant with the 95% compliance specification of NRS 048-2.

7.1.1 Redefining characteristic parameters

Current design parameters provided in NRS 034-1 are derived from 5 minute load data and are reflective of the maximum demand of the different customer classes. Because these parameters are based on the maximum demand, it is difficult for a designer to establish the compliance expected as load magnitude is not the sole factor affecting voltage drop.

A new set of design parameters were derived for this investigation. The design parameters were calculated to meet the 95% compliance criterion of NRS 048-2 and therefore do not necessarily have to coincide with the maximum demand. Load data averaged over 10 minutes was used to derive the parameters. This is in accordance with the QoS voltage evaluation method which requires the use of voltagerecordings averaged over 10 minutes.

Because of the short coming of calculating voltage drop at 10% design risk the new QoS parameters were derived using different combinations of risk-to-violations with a maximum risk of 5% being used. Each combination was calculated to meet the 95% compliance. The combinations used were:

1. 0.1% risk -to- 99 violations
2. 2.5% risk -to- 52 violations
3. 5.0% risk -to- 0 violations

It was found that combination 1 produced QoS design parameters which lead to the highest voltage drop estimates out of the 3 combinations, making them the most conservative. The QoS parameters derived using combination 2 were the least conservative.

The QoS parameters were also derived using a linear feeder topology and an asymmetrically branched feeder topology. QoS parameters calculated using the feeder topology produced more conservative designs compared to QoS parameters calculated from the branched feeder arrangement.

Overall, it was concluded that these new parameters were more representative of residential load compared to the original design parameters which only considered that load at the time of maximum demand.

7.1.2 COV curves

COV curves were then derived using the QoS design parameters. Using a COV curve, network designers can use the ADMD of a community to be electrified to find the coefficient of variation γ corresponding to the appropriate QoS design parameters for that community. The standard deviation, σ, can be calculated from $\gamma=\sigma/\mu$ where μ is the ADMD. The QoS Beta parameters α_{qos} and β_{qos} can be calculated from σ and μ using equations 2.3 and 2.4.

It was established that grouping consumers by income class or geyser penetration resulted in weak correlations of QoS parameters on the COV plot. Using combination 3, a correlation of 92% was found for points categorized by $\gamma<1.5$ and $\mu/c > 0.14$. The equation of the curve fit to these points is $\gamma = 13.837\left(\frac{\mu}{c}\right)^2 - 8.4614\left(\frac{\mu}{c}\right) + 1.8675$. Points with $\gamma \geq 1.5$ and $\mu/c < 0.14$ produced negligible correlations. This loss of correlation at the lower μ/c values is speculated to be a result of the higher degrees of load current distributions prevalent in the low income communities represented by these points.

The correlations of the COV curve might improve further if data pertaining to appliance penetration in the communities was available to allow for further classification. An available option is to classify customers based on load profiles as is practiced in the liberalized electricity market in order to design tariff structures. This approach would have a better chance of reducing degrees of skewing as it groups customers based on similar electricity usage patterns and magnitudes, hopefully resulting in an increase in correlation of design points. The main drawback of this approach is that at the design stage load profiles of un-electrified households are unknown. Since there is likely to be more than one COV curve if this approach was taken, this lack of information on customer type makes it difficult for designers to make a decision on which COV curve would be most appropriate base the design.

Using the BPP to analyze the performance of the derived curves, the COV curve $\gamma = 13.837\left(\frac{\mu}{c}\right)^2 - 8.4614\left(\frac{\mu}{c}\right) + 1.8675$ derived from the points categorized byγ$\gamma \leq 1.5$ and $\mu/c > 0.14$was found to best represent all the load classes including those at $\mu/c \geq 0.14$ and $\gamma \geq 1.5$. Therefore, the lack of correlation found in these points is negligible when working with this COV curve. The COV curves for 0.1% risk -to- 99 violations and 2.5% risk -to- 52 violations were found to be more likely to underestimate the expected voltage drops, particularly for rural areas or other low income areas with expected loads of μ/c ~< 0.14.

7.2 RECOMMENDATIONS FOR DESIGN PARAMETERS

The hypothesis of the investigation was:

A process to select a set of simple parameters representing the load for the purposes of economic LV residential network planning and design can be derived that will allow quality of supply specifications to be satisfied.

The research has validated this hypothesis.

Based on the achieved results, it is recommended that the COV curve $\gamma = 13.837\left(\frac{\mu}{c}\right)^2 - 8.4614\left(\frac{\mu}{c}\right) + 1.8675$ be used to derive design parameters for electrification design purposes.

This curve derived from grouping data based on $\mu/c \geq 0.14$ and $\gamma \leq 1.5$ was found to be able to cater for all income groups regardless of HWC/geyser penetration. It is also recommended that the 5% design risk be adopted as the voltage calculation standard. This recommendation is based on the finding that parameters based on the 5% risk-0 violation produced the COV curve with the highest correlations that can cater for communities in all income divisions. Also, in order to stay within compliance limits no more than a 5% design risk should be used to calculate voltage drop.

Designers are also encouraged to exploit branched feeder topologies as this has been proven to reduce voltage drop levels expected along the feeders.

7.3 OBSERVATIONS AND RECOMMENDATIONS FOR NETWORK VOLTAGE QoS ASSESSMENT MEASUREMENT TECHNIQUES

This investigation has brought to light some shortcomings of the current NRS 048-2 standard. These include:

1. Assessment period

   NRS 048-2 stipulates a minimum of 1 week to be used to assess the voltage regulation performance of a network but there is no mention for when in the year to carry out this assessment. Giving utilities the freedom to select the assessment week at any random period of the year to evaluate the power quality in terms of voltage regulation is not advised. From the South African data it was found that the months incurring the highest number of voltage violations were the same months within which the maximum demand occurred. Therefore, if the QoS assessment is carried out during an off peak period of the year the quality assessment might produce more optimistic results that are not representative of the worst case conditions occurring in the peak periods.

   The maxima used in this research occurred in various months of the year due to the attempt to find a healthy worst week sample, i.e. constituting of 30 or more households. It is however recommended that the assessment week be selected during the winter or summer season depending on the climatic zone. This is because cold conditions have been found to be highly loaded as there is an increase in the use of appliances such as geysers, heaters, central heating etc which are major power consumers and, in some climatic regions, the peak load is due to air conditioning in summer.

The implications of measuring over a long term assessment period, i.e. more than 1 week, have not been reviewed in this investigation. However it is expected that the network performance would be rated differently when assessing over a week compared to a longer period. It is recommended that a single period be prescribed to evaluate voltage regulation compliance.

2. <u>Average Time</u>

   Load data averaged over 10 minutes was used in this research as this is the same averaging period used for voltage measurements used for voltage QoS assessment, as required by the current version of NRS 048-2.

   Based on the work of Wright and Firth [2007], Herman and Kritzinger [1993] and Widen et al [2010] it is apparent that this 10 minute averaging interval will result in underestimates of voltage drop along the feeders, as the magnitude of load is lowered. Using the load research data, the effects of averaging over 5-, 10- and 20minute data on the maximum voltage drop was examined. The maximum expected voltage drops derived from 10 minute and 20 minute data were compared to those calculated using 5 minute data. The calculations were done using 0.1% risk as calculating at 0% risk is not possible when using the Herman Beta algorithm. The table of results is given in appendix F.

   The results show that, compared to voltage drop estimates calculated using 5 minute data, averaging over 10 minutes will result in voltage drop estimates reduced by 6.85%. Averaging over 20 minutes brings down voltage drop estimates by 11%. Data of a higher resolution than 5 minutes was not available for this research. Therefore, to make a recommendation of moving to 5minute data would be premature at this stage. It is recommended that a survey of appliance penetration be taken and the tolerance of the appliances to the magnitude and duration of voltage levels lower than the rated voltages be investigated. This would give a better idea of the appropriate averaging time to use with regards to the voltage limits.

However, since the aim is to translate QoS specifications into design parameters, it is recommended that when an appropriate averaging period is agreed upon for the load data that period should

also be used to average the data used for QoS assessment.

3. The constraint restricting 2 or more consecutive 10 minute periods surpassing compliance limits

   An additional constraint for supply voltage by NRS 048-2 is that 2 or more consecutive 10 minute periods are not allowed to be above the compliance limits. In this investigation, 20 minute data was taken to represent 2 consecutive 10 minute periods and it was found that this data predicted voltage violations about as frequently as the 10 and 5 minute data. This is attributed to the fact that voltage drop is related to the magnitude of load and the load dispersion which can be present for periods longer than 10 minutes. This constraint needs revision. A recommendation would be to include a voltage magnitude constraint on this criterion that should not be surpassed. For example the average voltage drop for 2 consecutive 10 minute periods in violation,i.e. outside the compatibility limit of 10%, should not exceed the voltage limit of 15%.

7.4 FINAL THOUGHTS

The revision of current standards is called for to address the issues highlighted in this investigation. This action will go a long way to ensure customers are provided with electricity of sufficient quality at a constantly low cost to the utility.

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APPENDIX A

1	2	3	4	5
Consumer load class	**Derivation of income**	**Description of dwelling**	**Type of road**	**Water reticulation**
Rural settlement	Mainly from pensions and subsistence farming. Some breadwinners work far away in cities.	Mainly based on traditional construction methods	Normally tracks with difficult access	Normally none
Rural village	From pensions and subsistence farming. Some breadwinners are employed in nearby industrialized areas and commute daily.	Mixture of modern and traditional construction methods	Mainly gravel with main roads tarred	Some communal standpipes
Informal settlement	From work in a nearby town or city – largely from the informal sector	A range, from shacks to newer "government subsidy" houses made from blocks. Self-build schemes fall into this category. Built area of dwellings generally less than 40 m^2.	A range, from tracks in informal areas to gravel in planned areas.	None in informal areas. Planned areas generally have water piped to a tap in the yard of each dwelling.
Township area	From work in cities or towns, pensions, and some informal employment	A range, from low-income flats to old township houses and newer government scheme houses (mid-range), to small semi-detached houses. Built area of dwellings generally from 50 m^2 to 80 m^2.	Mostly tarred	Piped to most houses – half of which eventually have working electrical hot-water cylinders.
Urban residential I	From blue-collar jobs in cities	Houses that range in size from 80 m^2 to 170 m^2. Most houses have some visible repair or maintenance work in progress.	All tarred	Piped to all houses.
Urban residential II	From formal employment in cities, mostly white-collar jobs	The built area of main dwellings is typically 190 m^2. None of the houses are multi-storey.	All tarred	Piped to all houses, all of which have electrical hot-water cylinders.
Urban township complex	Mainly from professional jobs in cities, level of employment is high.	Normally very high density, in complexes that incorporate security or other shared services. Dwellings are single or multi-storey. Floor area in the range from 80 m^2 to 150 m^2 per unit.	All tarred	Piped to all houses. A high percentage of such houses have multiple electrical hot-water cylinders.
Urban multi-storey/estate	Mainly from professional jobs in cities, level of employment is very high.	Large, constructed of brick or concrete, floor area from 250 m^2 to 500 m^2. In regions with some desirable natural feature (e.g. a view).		

Figure A1: Classification of domestic consumers - Description of consumer load classes [NRS 034-1, 2007]

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Current type			Load parameters – 7 years[c d e f]						Load parameters – 15 years[c d e f]					
Consumer class	**AMPS**[a] **and LSM**[a] **class**	**Income range**[b] (gross R/month)	*a*	*b*	*c*	**ADMD** kVA	*μ* A	*ó* A	*a*	*b*	*c*	**ADMD** kVA	*μ* A	*ó* A
Rural settlement	LSM 1 (low end)	0 to 600	0,30	2,98	20	0,42	1,83	2,78	0,35	2,88	20	0,50	2,17	3,03
Rural village	LSM 1 and 2	400 to 900	0,43	2,52	20	0,67	2,91	3,55	0,48	2,13	20	0,84	3,65	4,07
Informal settlement	LSM 3 and 4	800 to 1 500	0,77	9,88	60	1,00	4,35	4,56	0,91	8,80	60	1,30	5,56	5,36
Township area	LSM 5 and 6	1 500 to 3 000	1,05	7,81	60	1,64	7,13	6,18	1,22	5,86	60	2,37	10,30	7,96
Urban residential I	LSM 7	3 000 to 5 500	1,23	5,56	60	2,50	10,87	8,28	1,25	3,55	60	3,59	15,61	10,93
Urban residential II	LSM 7 and 8	5 500 to 8 500	1,45	6,07	80	3,54	15,39	10,81	1,42	4,10	80	4,72	20,52	13,68
Urban township complex	LSM 8	8 500 to 12 000	1,45	5,75	80	3,70	16,09	11,20	1,42	4,13	80	4,70	20,43	13,63
Urban multi-storey/estate[f]	LSM 8 (high end)	12 000 to 24 000	1,43	4,41	80	4,50	19,57	13,15	1,37	3,39	80	5,30	23,04	15,09

[a] Living standards measure (LSM) as quoted in the All Media and Product Survey (AMPS) conducted annually by the South African Advertising Research Foundation.

[b] Average household income ranges shown for comparative purposes are in 2005 Rands. Any income data collected at a later date should be deflated by the CPI to allow a direct comparison.

[c] If the target community matches the description, but the chosen value of *c* is different, new *a* and *b* values can be calculated for the chosen value of *c*, using the formula given in B.4.3.

[d] Parameters have been normalized to the climate in the interior of South Africa where the winters are generally cold and with low rainfall. In regions where the winter is cold and wet (e.g. Cape Peninsula), the ADMD is about 12 % higher than that given. In climates similar to that of the Durban coastal region, the ADMD is about 12 % lower than that given.

[e] Except as indicated in f below, the parameters have been derived from carefully monitored case studies around the country, and reflect best knowledge at the time of publication of actual consumer demand over time. The actual load parameters used depend upon the strategy of the planner with regard to phasing of capital expenditure.

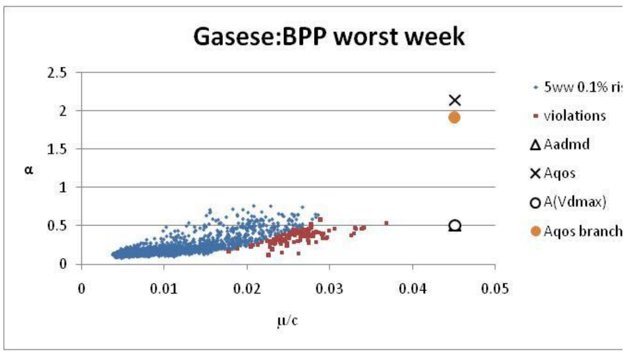
[f] Parameters for this consumer class have been extrapolated from existing data, since no sample load data have yet been collected from such consumers. Loads significantly higher than the ADMD shown in LSM 8 (high end) can be expected in the case of specific high-consumption developments. In such cases, estimated load data should be obtained from the relevant local authority or licensee.

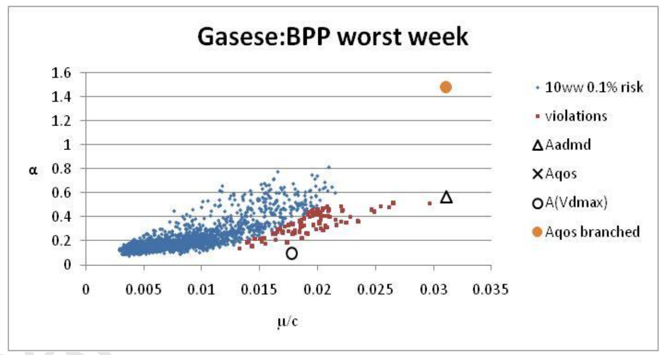
Figure A2: Classification of domestic consumers – Typical design load parameters for domestic consumers [NRS 034-1, 2007]

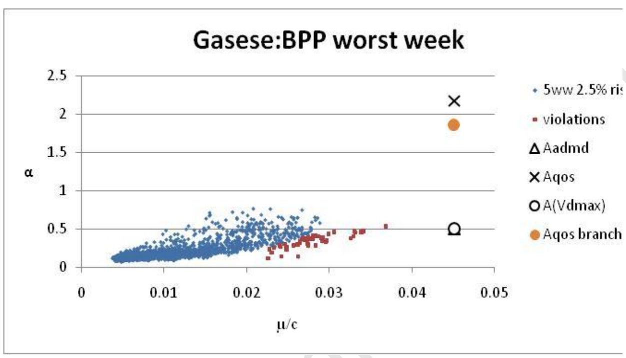
APPENDIX B

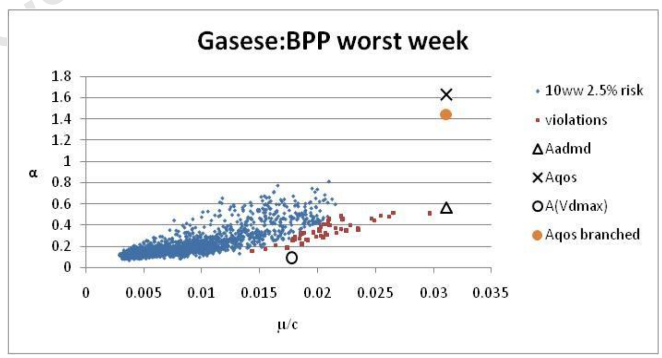
This appendix shows the Beta Parameter Plots for all measured communities. Each plot displays:

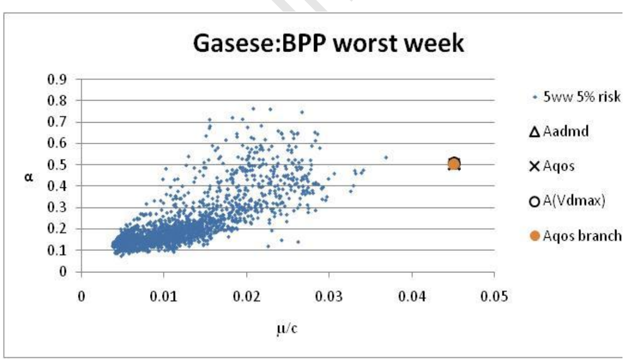
- The load points producing the voltage drop violations required to meet 95% compliance
- The QoS parameters for the linear (α_{qos}) and branched networks ($\alpha_{qos(branched)}$)
- The load point at maximum demand (α_{admd})
- The load point at maximum voltage drop (α_{Vdmax})

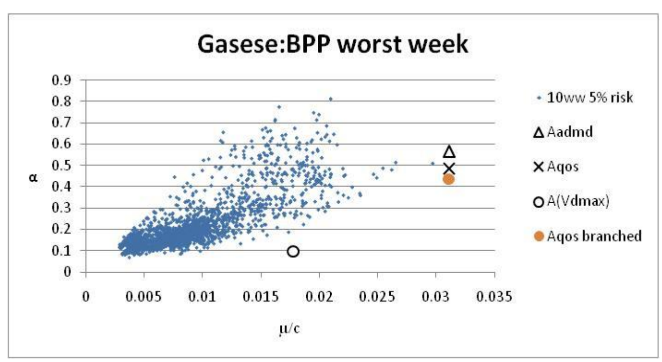


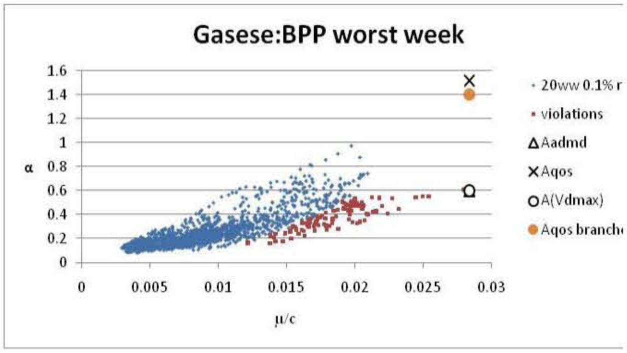


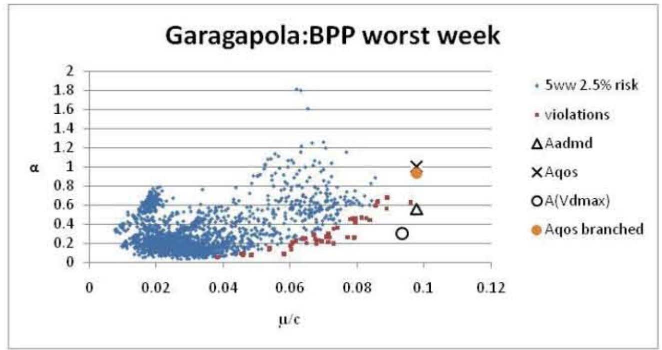


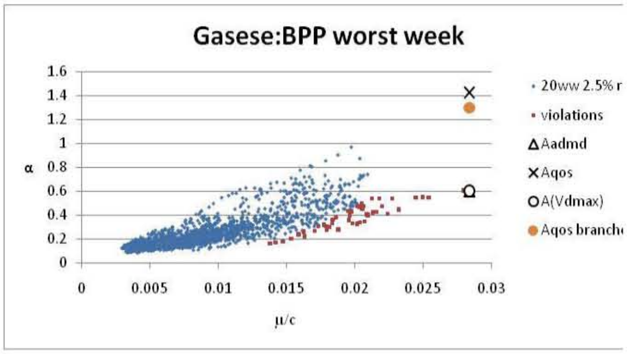


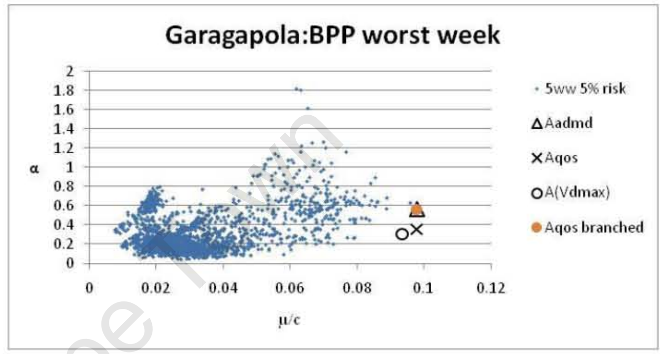


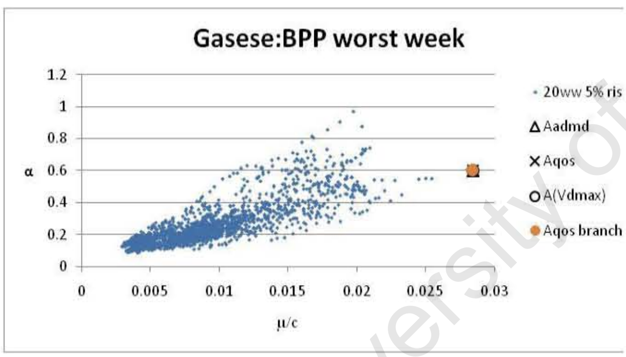



Gasese:BPP worst week
α
μ/c
20ww 0.1% r
violations
Aadmd
Aqos
A(Vdmax)
Aqos branch


Garagapola:BPP worst week
α
μ/c
5ww 2.5% risk
violations
Aadmd
Aqos
A(Vdmax)
Aqos branched


Gasese:BPP worst week
α
μ/c
20ww 2.5% r
violations
Aadmd
Aqos
A(Vdmax)
Aqos branch


Garagapola:BPP worst week
α
μ/c
5ww 5% risk
Aadmd
Aqos
A(Vdmax)
Aqos branched


Gasese:BPP worst week
α
μ/c
20ww 5% ris
Aadmd
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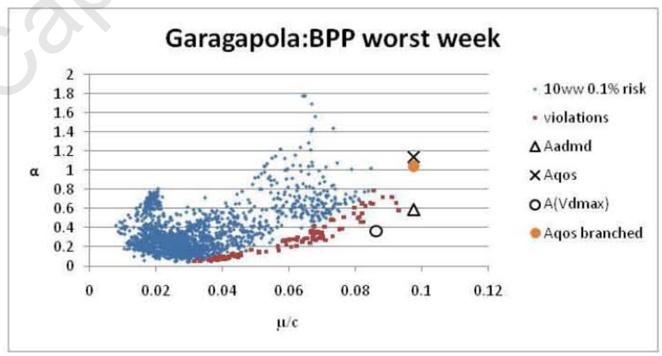
A(Vdmax)
Aqos branch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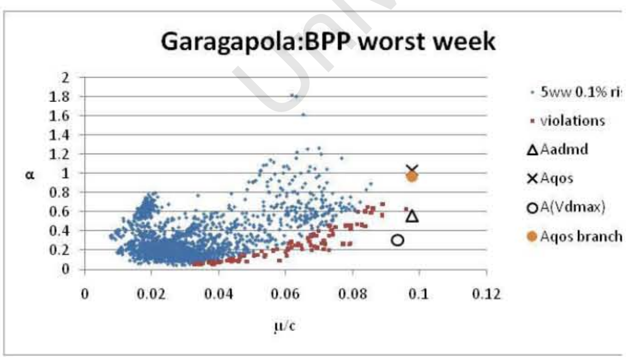
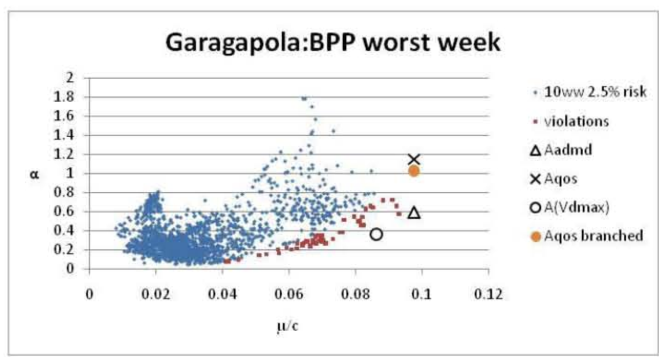
α
μ/c
10ww 0.1% risk
violations
Aadmd
Aqos
A(Vdmax)
Aqos branched


Garagapola:BPP worst week
α
μ/c
5ww 0.1% ri
violations
Aadmd
Aqos
A(Vdmax)
Aqos branch


Garagapola:BPP worst week
α
μ/c
10ww 2.5% risk
violations
Aadmd
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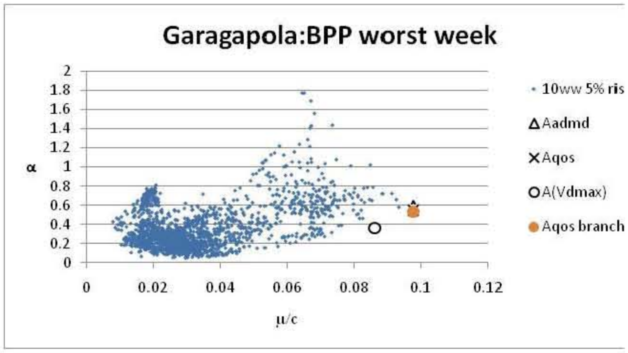
Aqos branched


Garagapola:BPP worst week
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μ/c
10ww 5% ris
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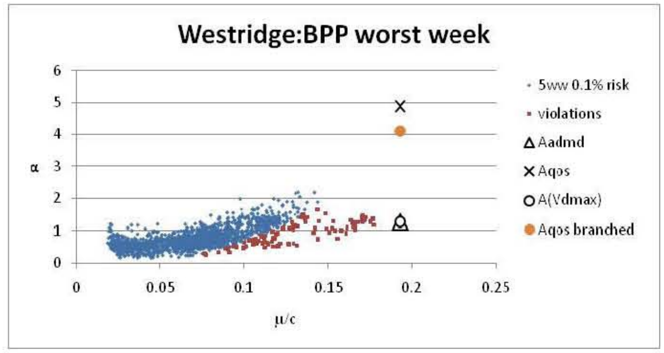
Aqos branch


Westridge:BPP worst week
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μ/c
5ww 0.1% risk
violations
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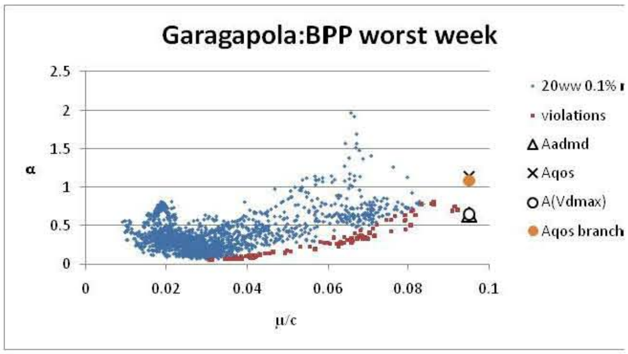
Garagapola:BPP worst week
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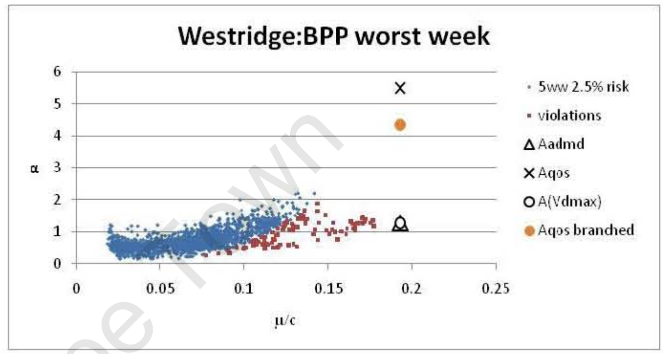
Westridge:BPP worst week
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μ/c
5ww 2.5% risk
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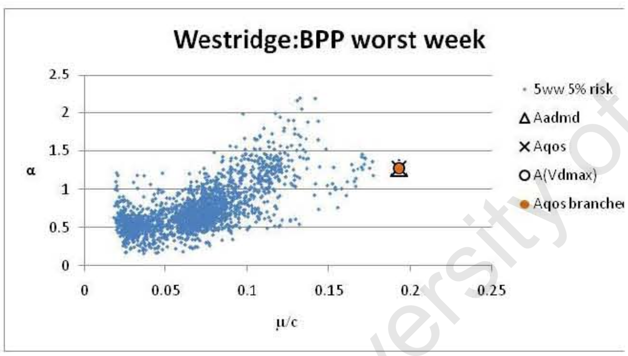
Westridge:BPP worst week
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5ww 5% risk
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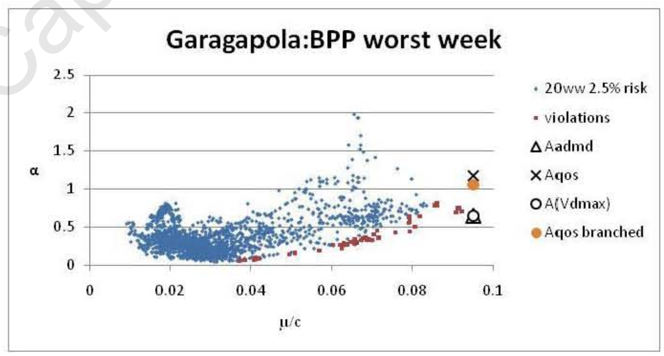
Garagapola:BPP worst week
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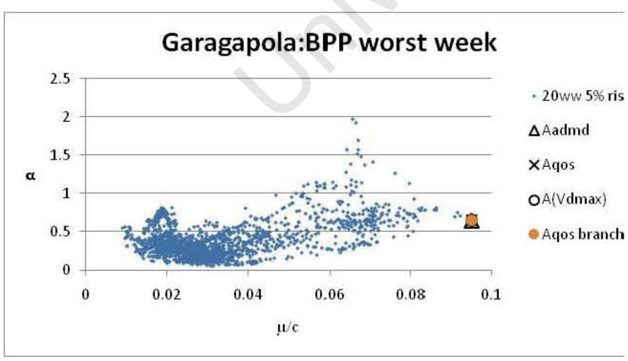
Garagapola:BPP worst week
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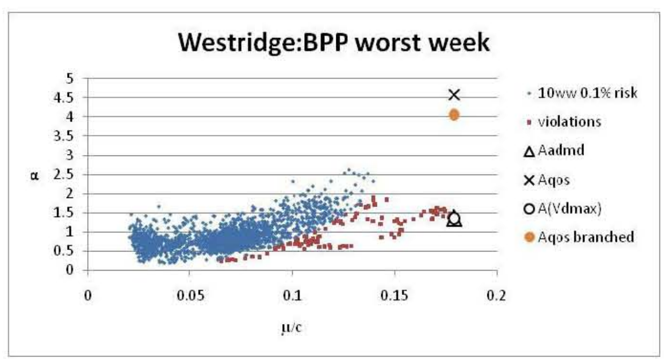
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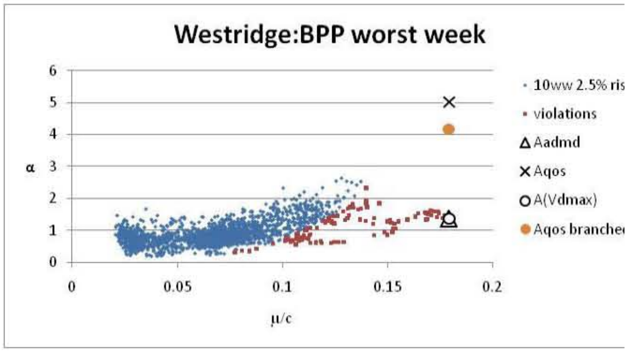
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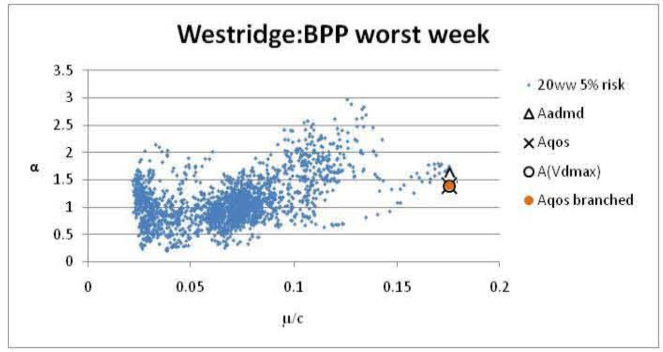
Westridge:BPP worst week
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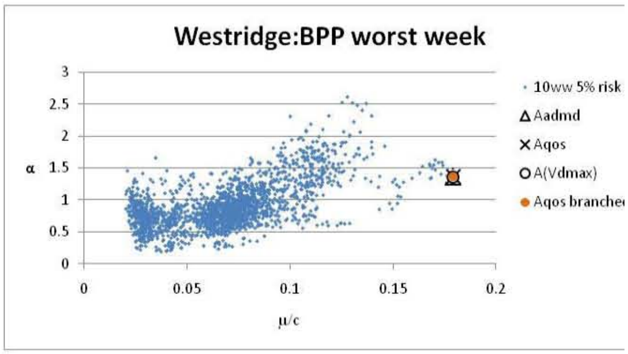
Westridge:BPP worst week
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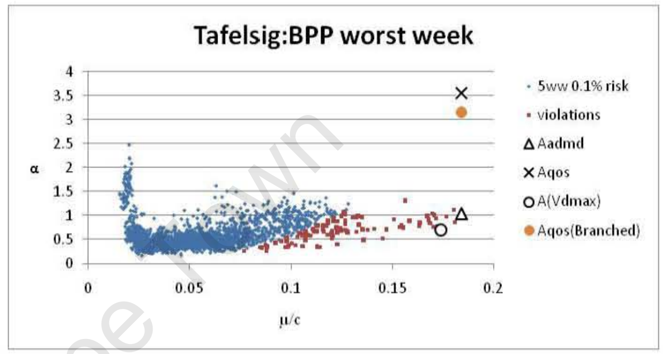
Tafelsig:BPP worst week
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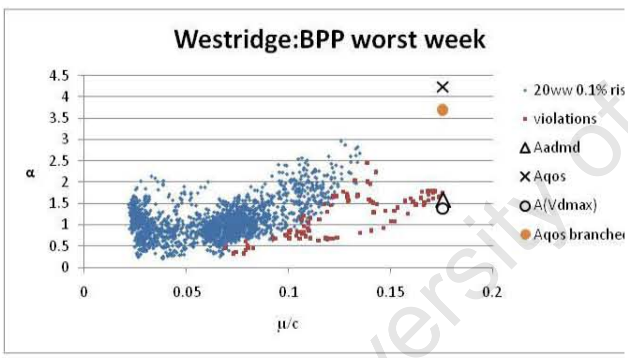
Westridge:BPP worst week
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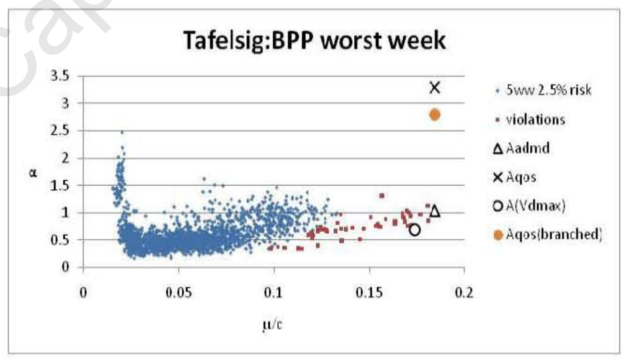
Tafelsig:BPP worst week
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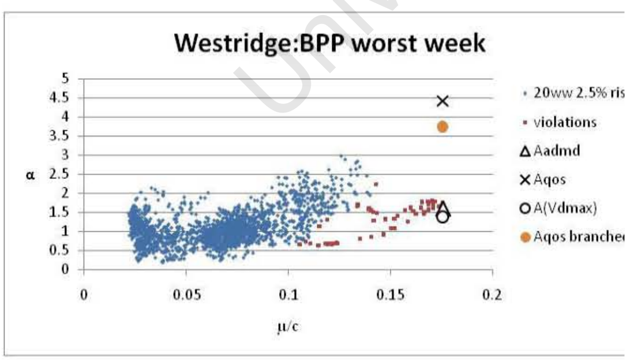
Westridge:BPP worst week
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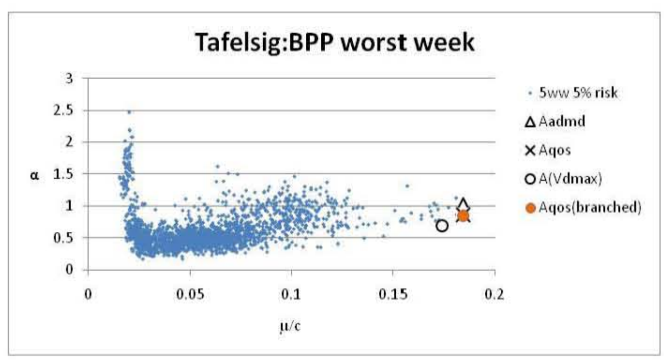
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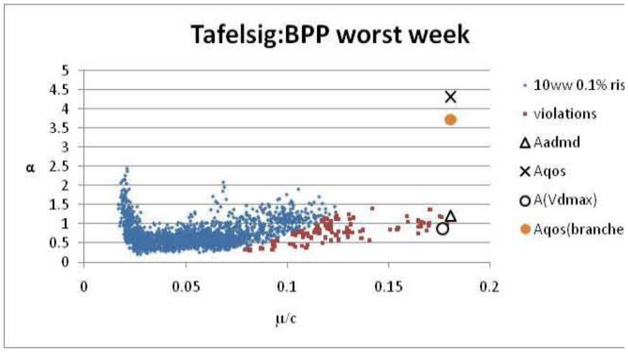
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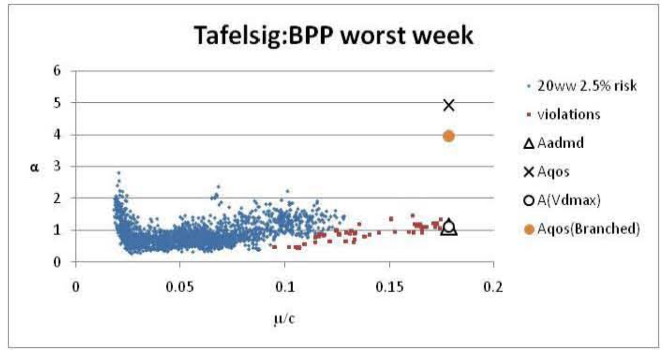
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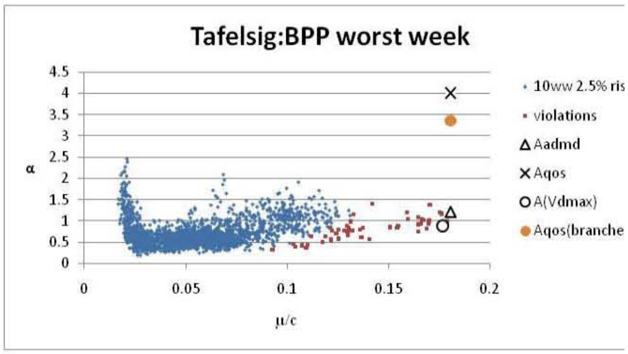
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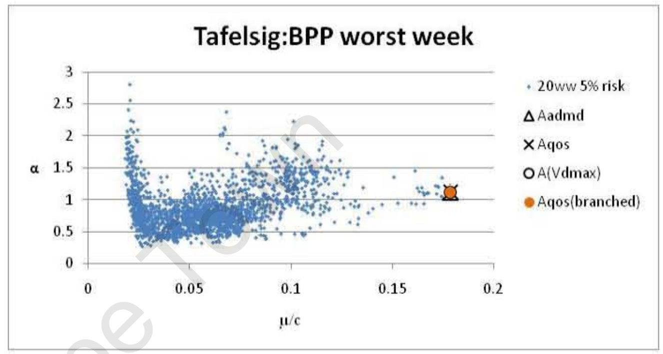
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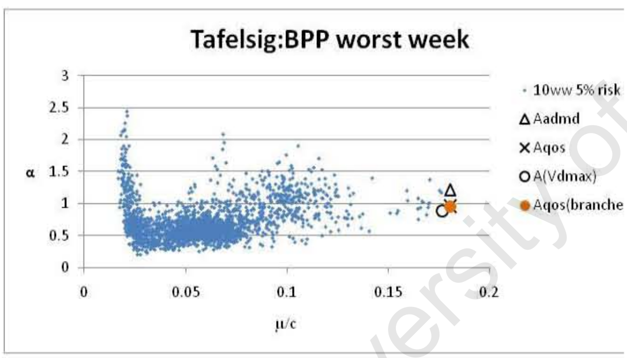
Tafelsig:BPP worst week
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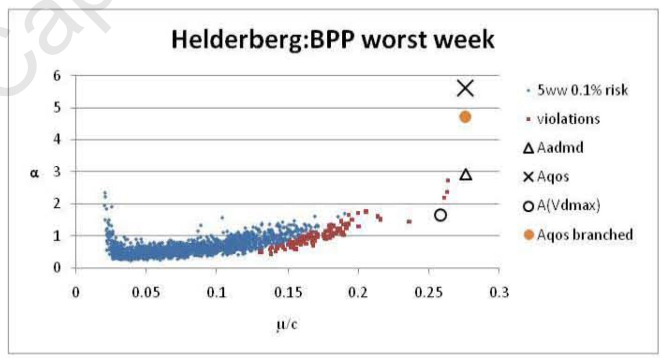
Helderberg:BPP worst week
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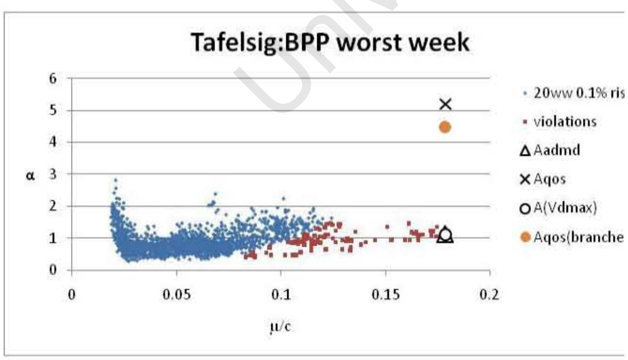
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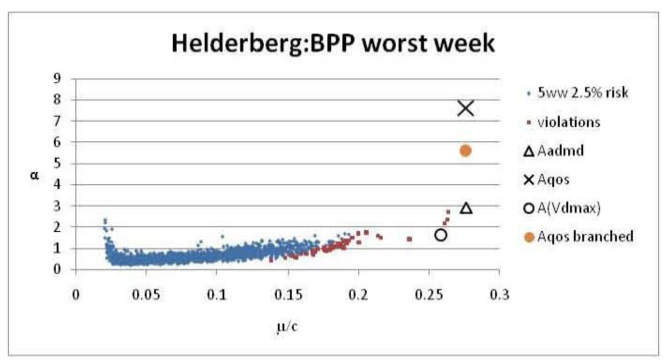
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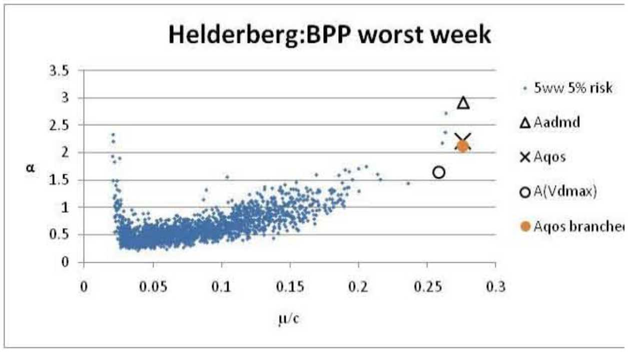
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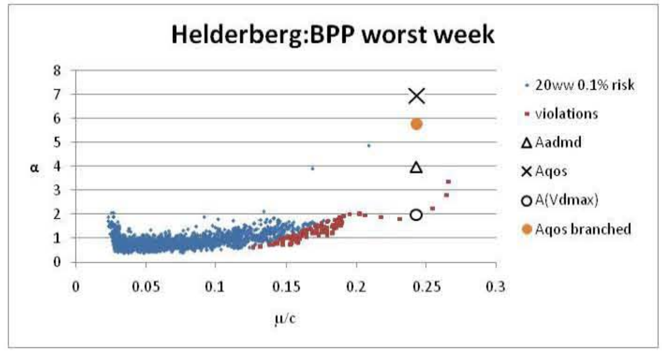
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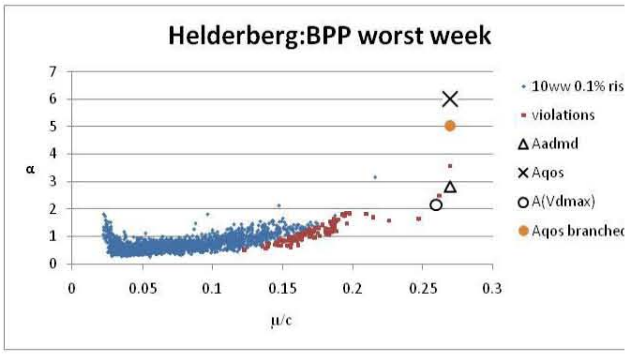
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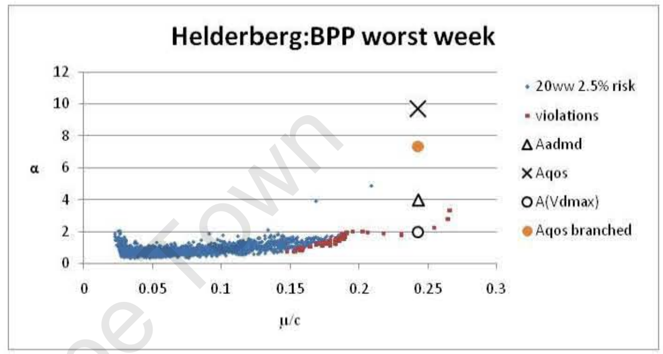
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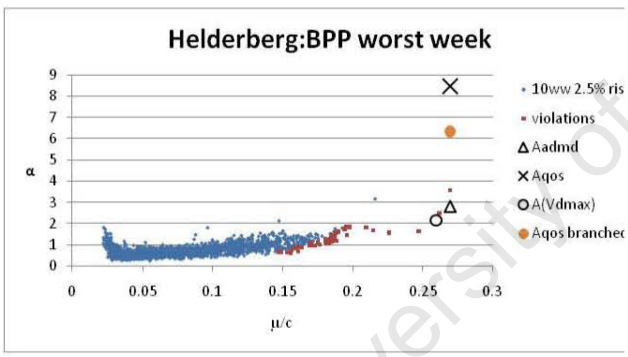
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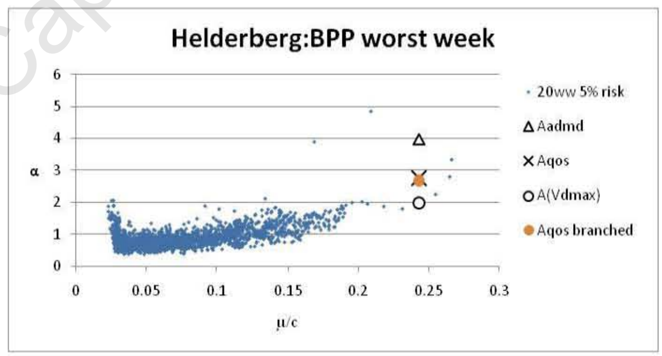
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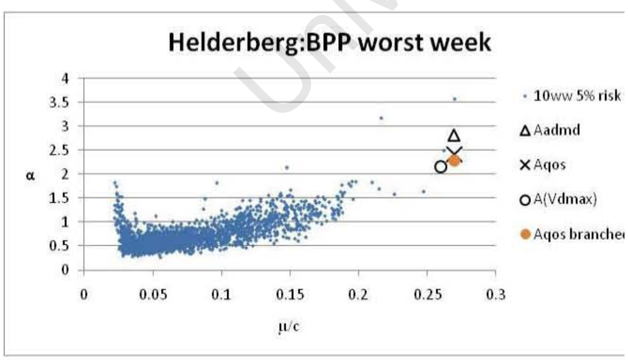
Helderberg:BPP worst week
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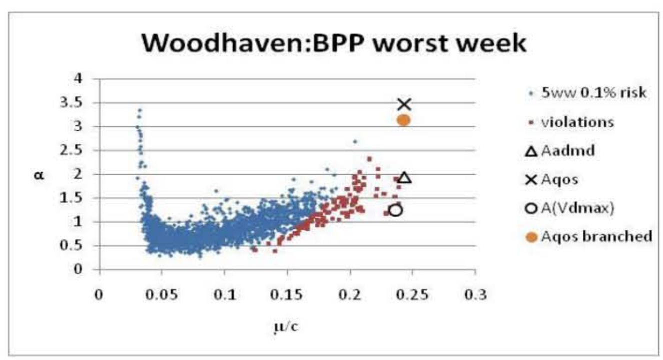
Woodhaven:BPP worst week
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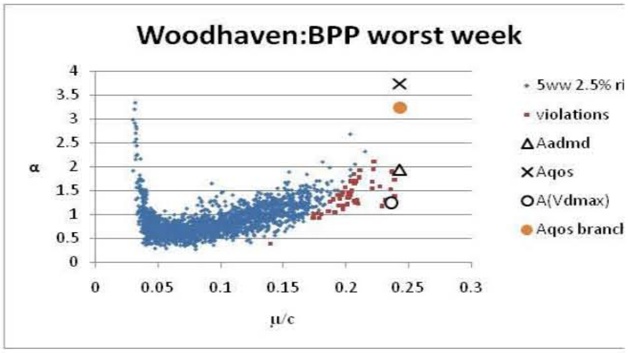
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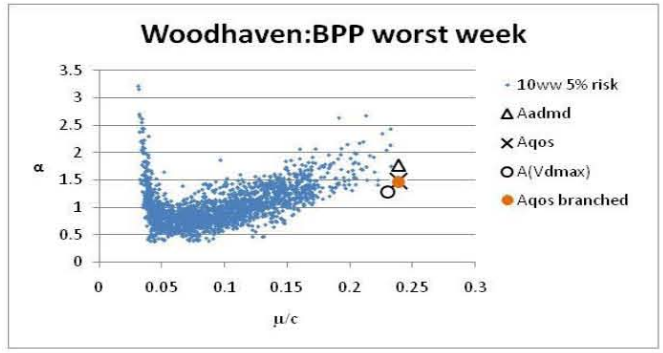
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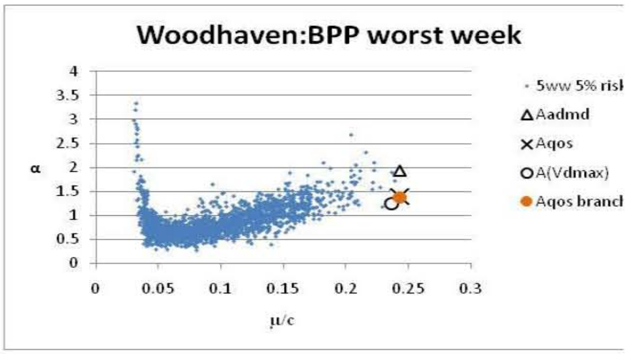
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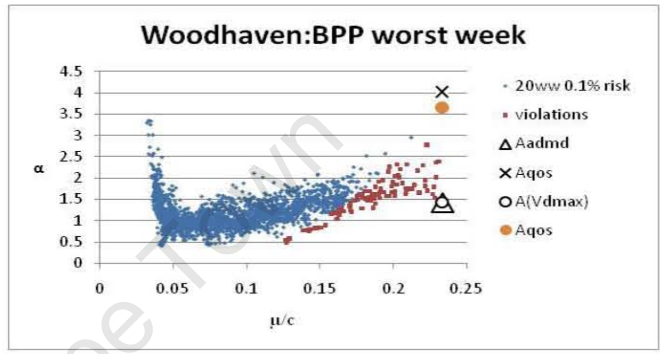
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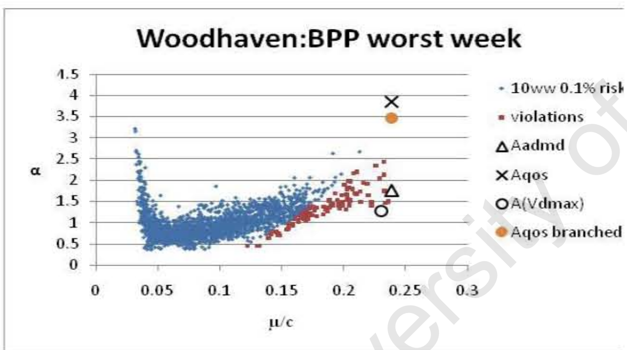
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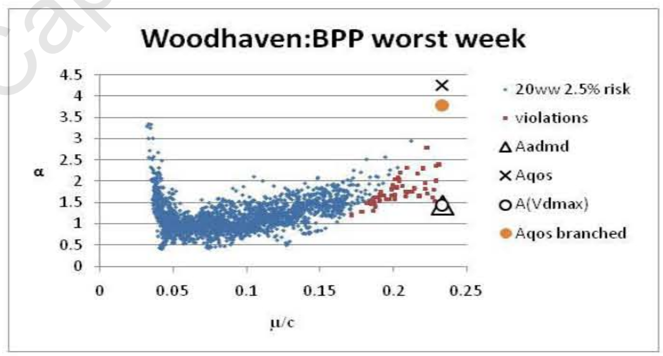
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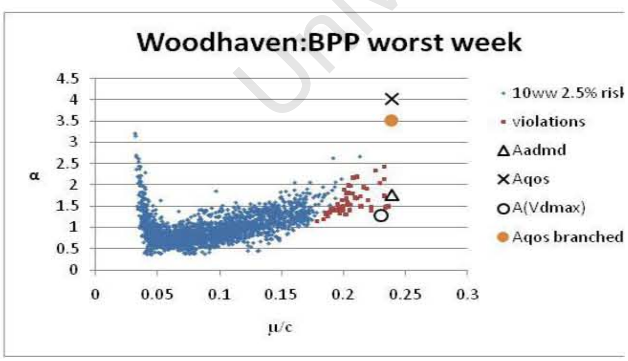
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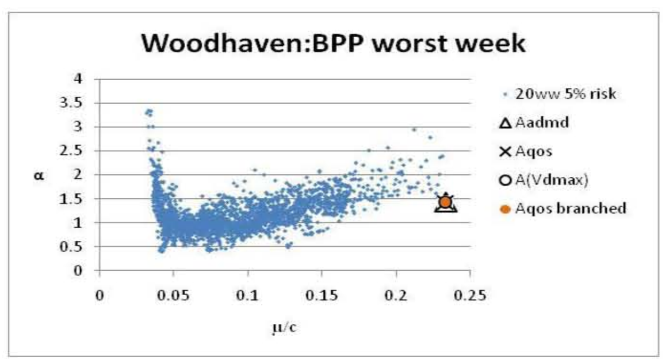
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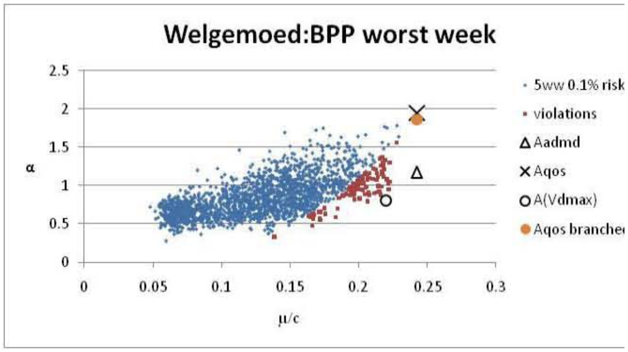
Welgemoed:BPP worst week
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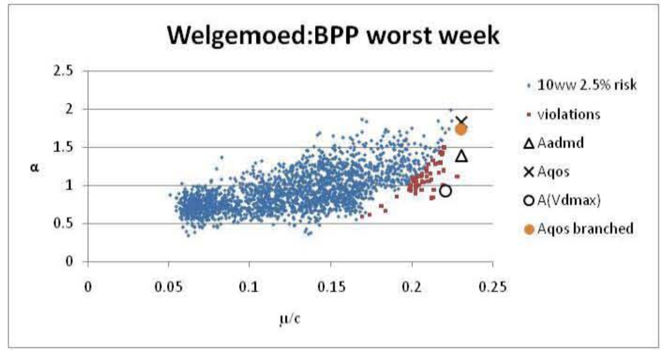
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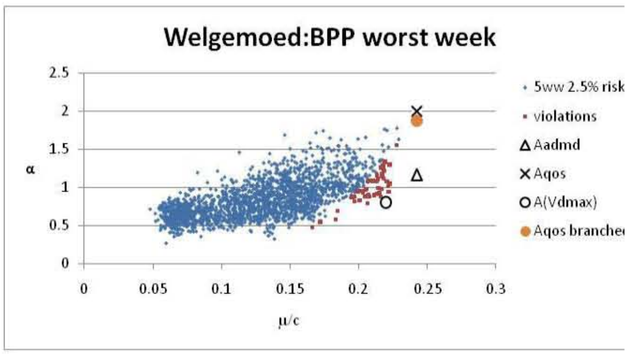
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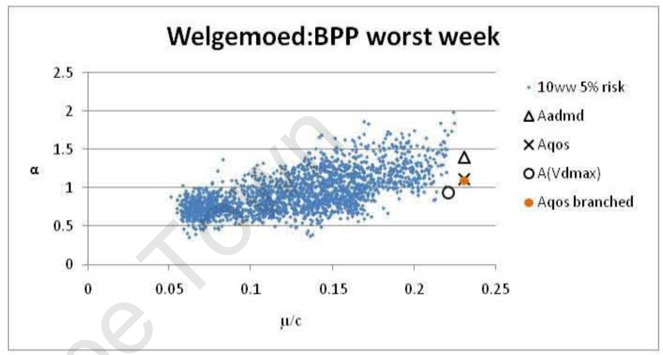
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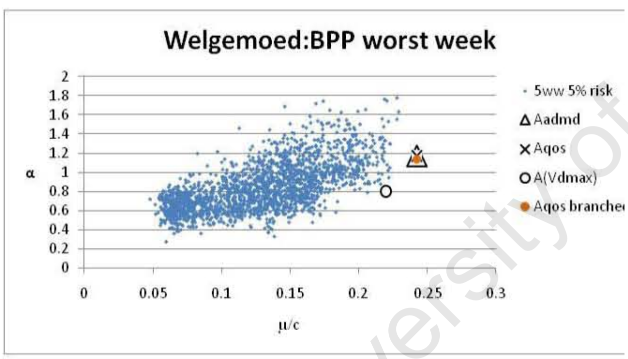
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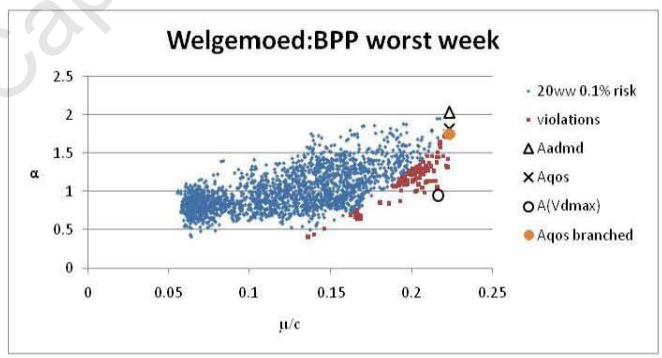
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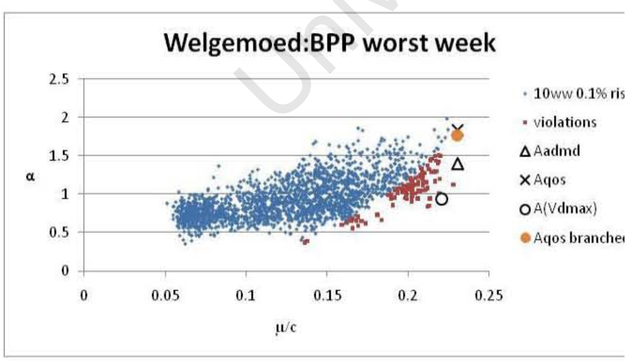
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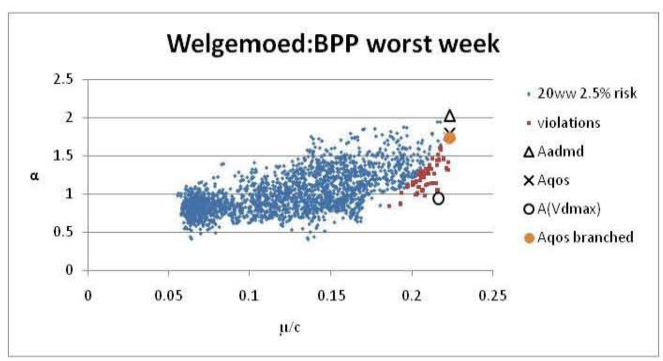
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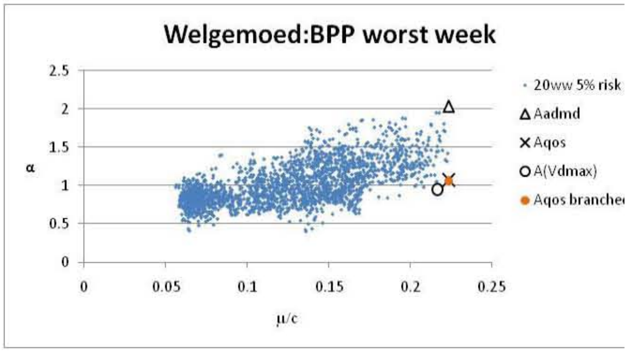
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20ww 5% risk
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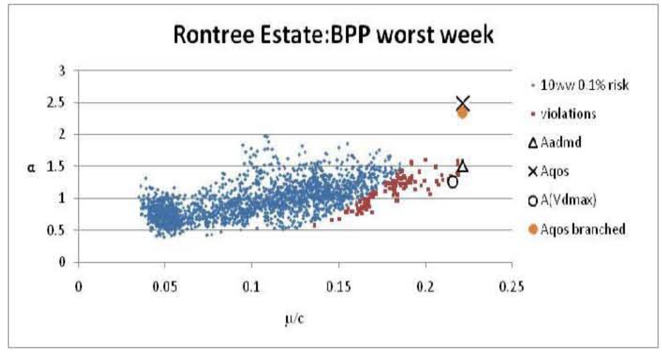
Rontree Estate:BPP worst week
10ww 0.1% risk
violations
Aadmd
Aqos
A(Vdmax)
Aqos branched
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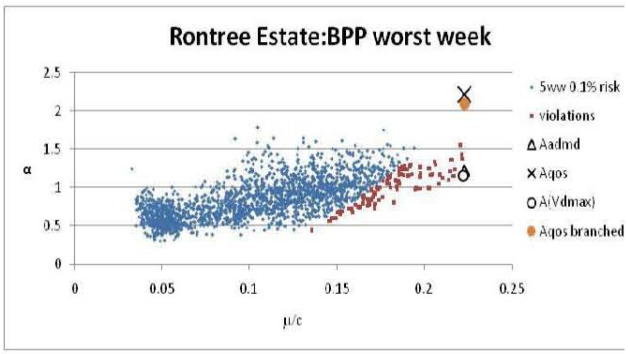
Rontree Estate:BPP worst week
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Aadmd
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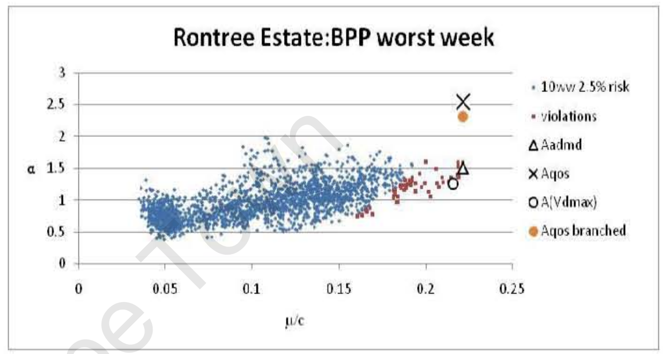
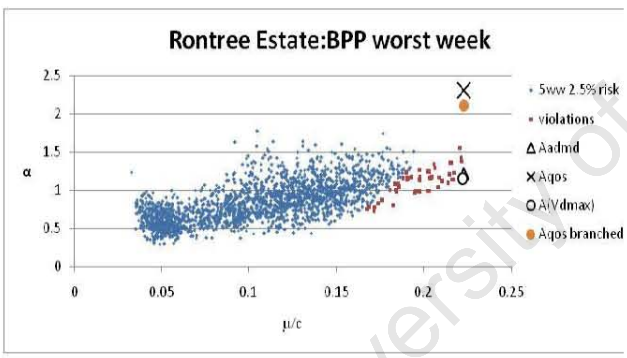
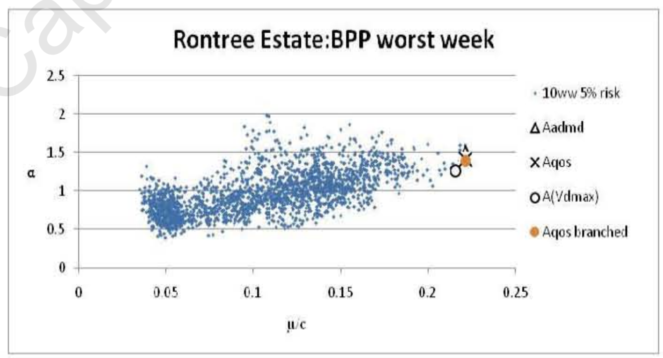
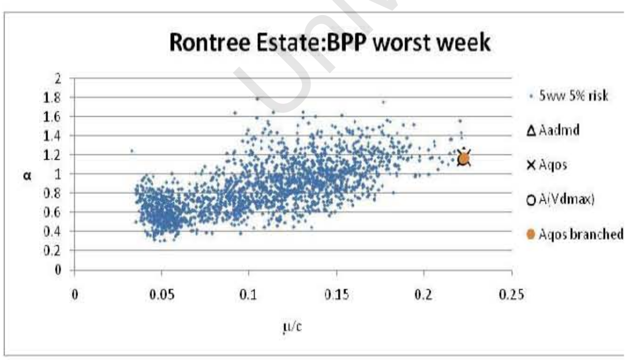
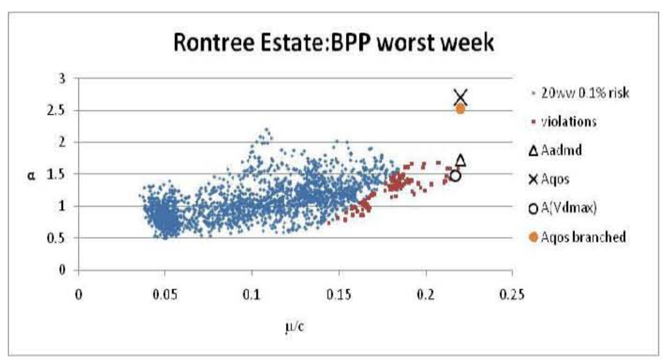
α
μ/c

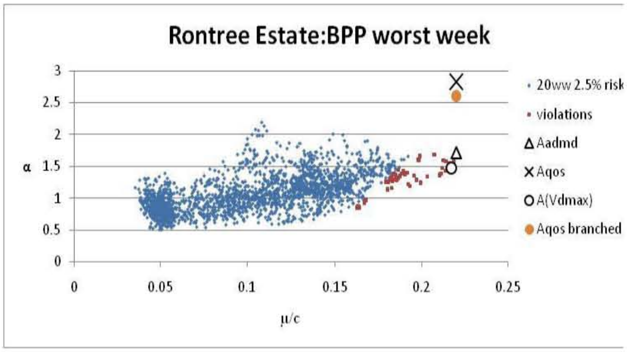

Rontree Estate:BPP worst week
10ww 2.5% risk
violations
Aadmd
Aqos
A(Vdmax)
Aqos branched
α
μ/c


Rontree Estate:BPP worst week
5ww 2.5% risk
violations
Aadmd
Aqos
A(Vdmax)
Aqos branched
α
μ/c

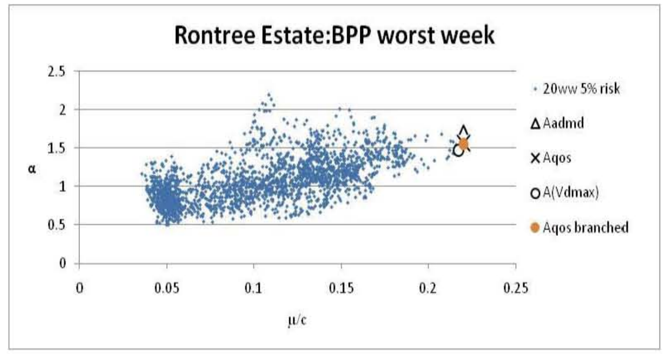

Rontree Estate:BPP worst week
10ww 5% risk
Aadmd
Aqos
A(Vdmax)
Aqos branched
α
μ/c


Rontree Estate:BPP worst week
5ww 5% risk
Aadmd
Aqos
A(Vdmax)
Aqos branched
α
μ/c


Rontree Estate:BPP worst week
20ww 0.1% risk
violations
Aadmd
Aqos
A(Vdmax)
Aqos branched
α
μ/c



Rontree Estate:BPP worst week
20ww 2.5% risk
violations
Aadmd
Aqos
A(Vdmax)
Aqos branched
α
μ/c

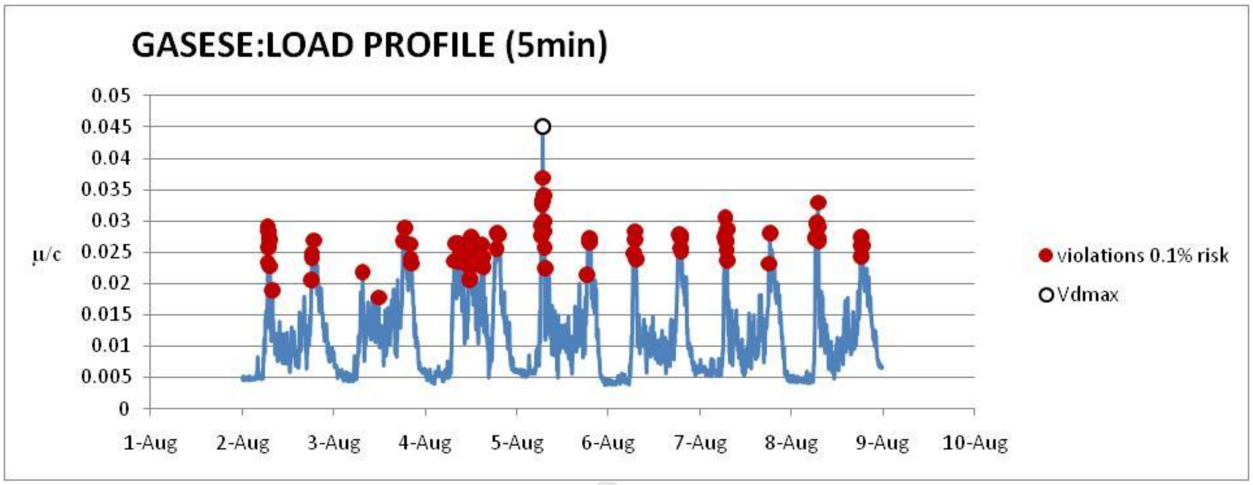


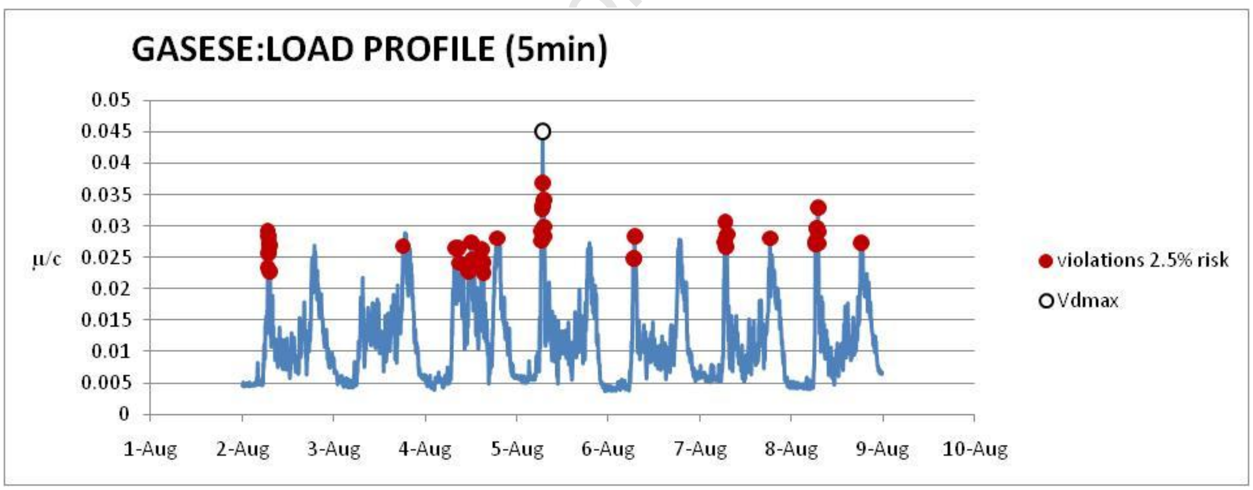
Rontree Estate:BPP worst week
20ww 5% risk
Aadmd
Aqos
A(Vdmax)
Aqos branched
α
μ/c

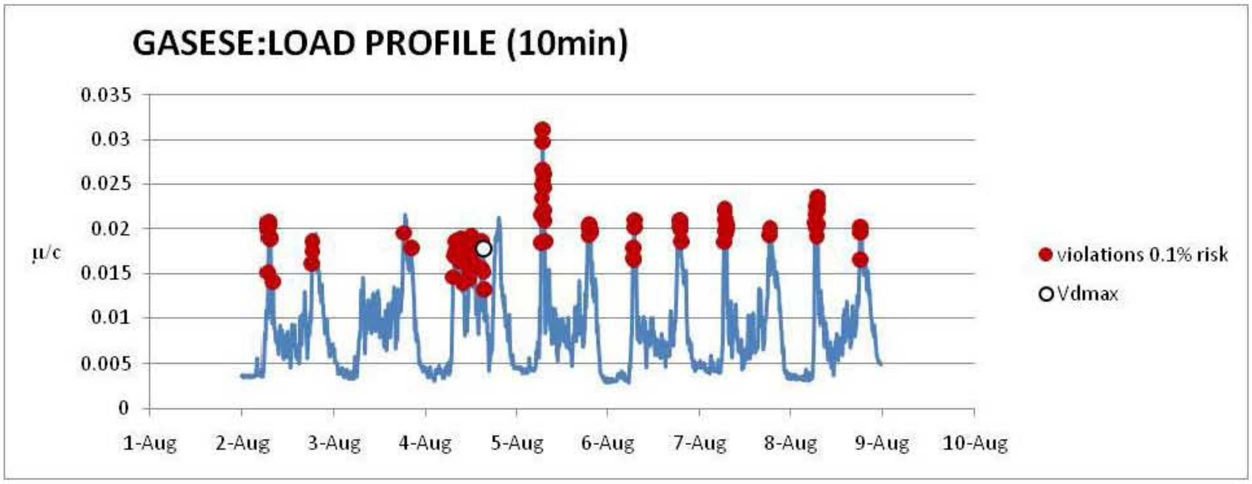
APPENDIX C

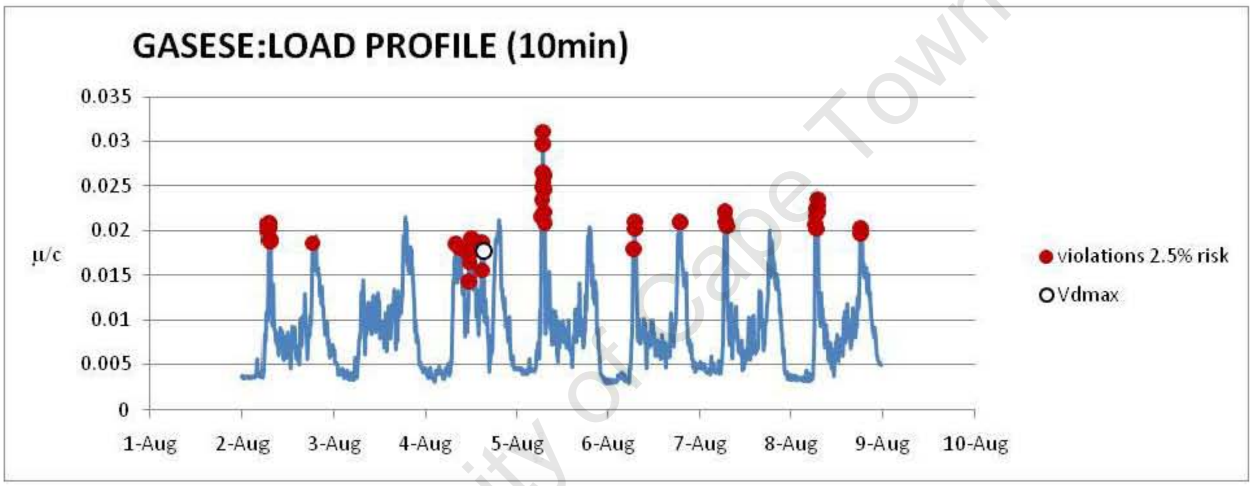
Appendix C shows the load profiles for each measured community. Each load profile displays the loads and times were each of the following events occurs:

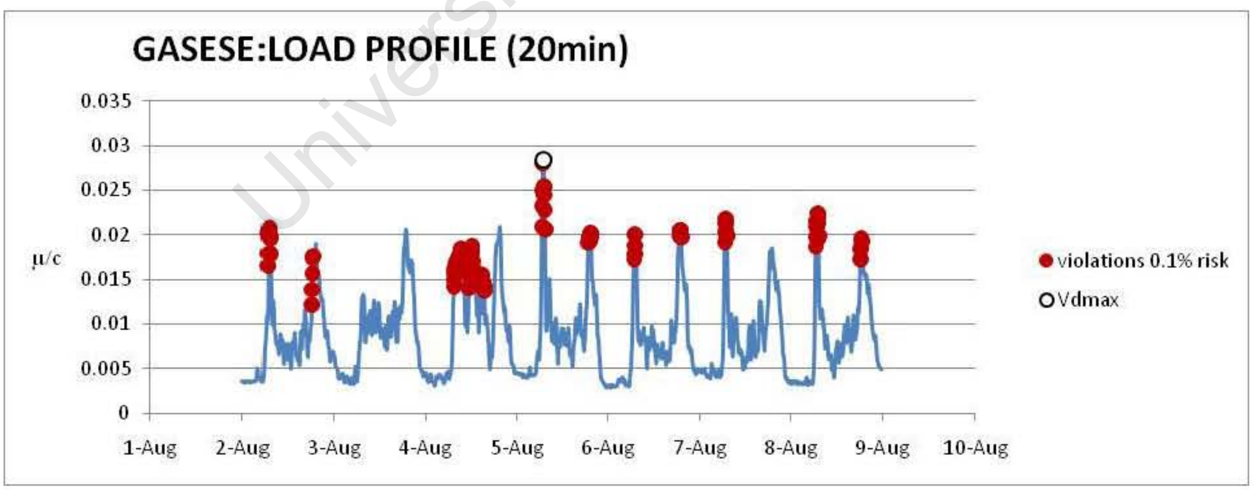
- the highest voltage drops allowed to meet 95% compliance
- maximum demand
- maximum voltage drop

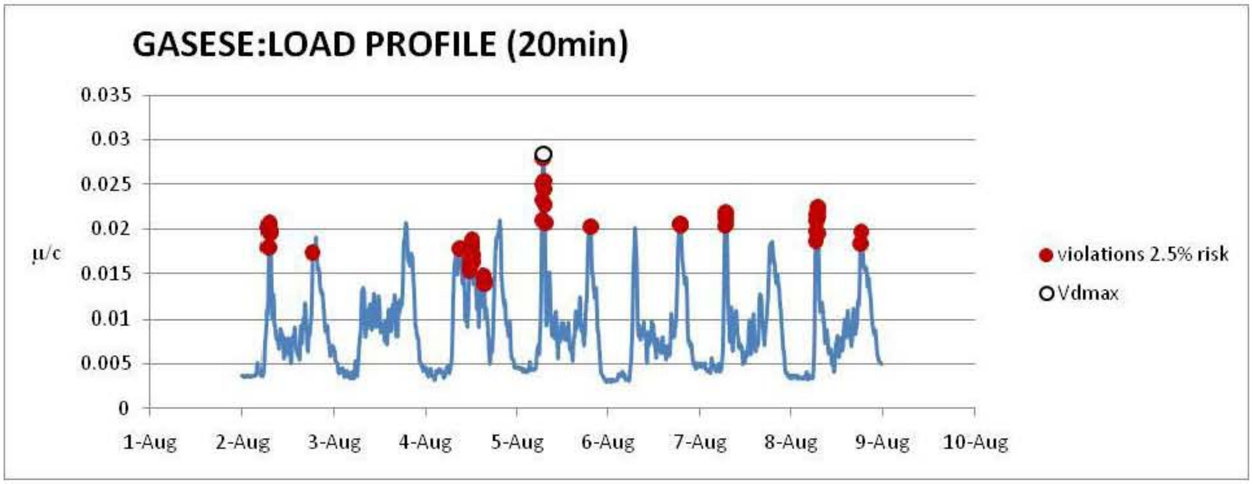


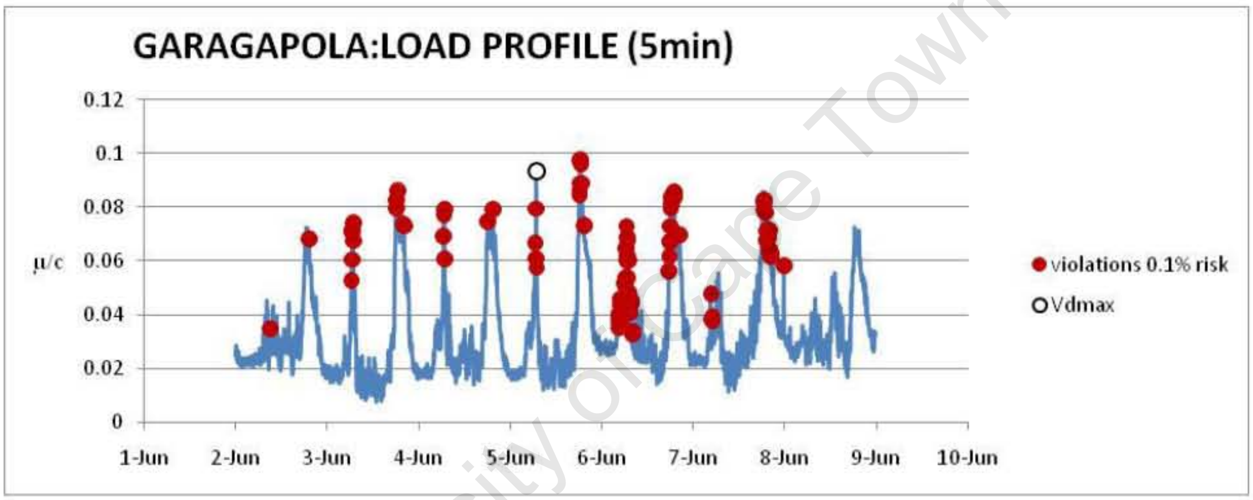


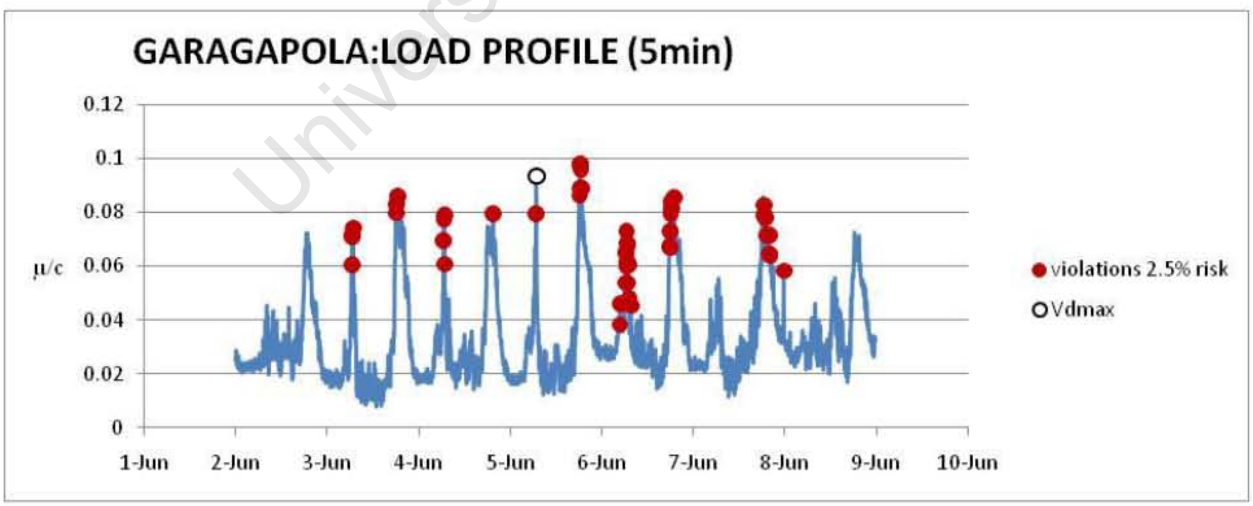

GASESE:LOAD PROFILE (10min)
0.035
0.03
0.025
0.02
0.015
0.01
0.005
0
µ/c
1-Aug
2-Aug
3-Aug
4-Aug
5-Aug
6-Aug
7-Aug
8-Aug
9-Aug
10-Aug
violations 0.1% risk
Vdmax

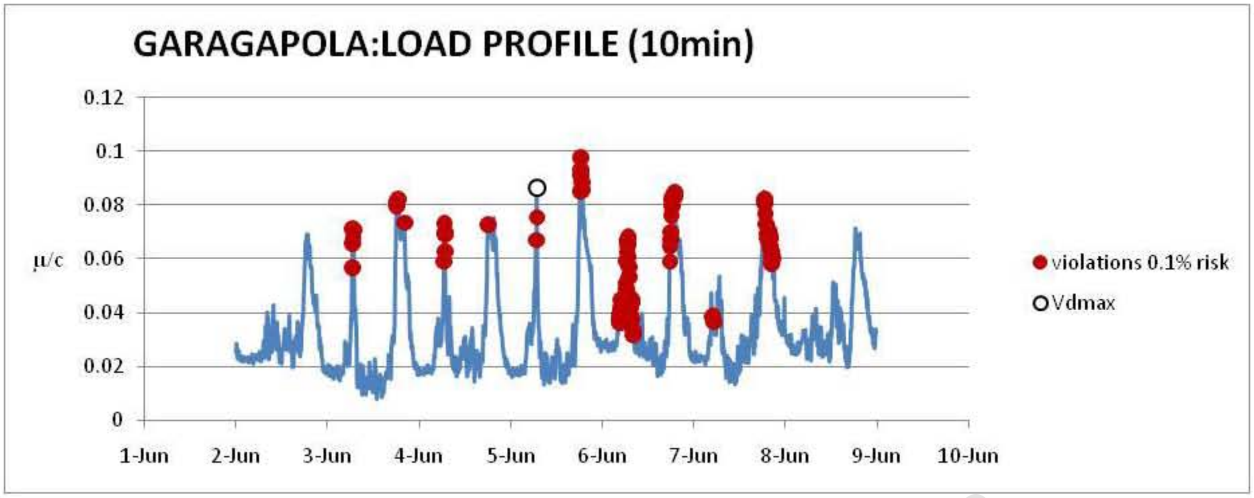

GASESE:LOAD PROFILE (10min)
0.035
0.03
0.025
0.02
0.015
0.01
0.005
0
µ/c
1-Aug
2-Aug
3-Aug
4-Aug
5-Aug
6-Aug
7-Aug
8-Aug
9-Aug
10-Aug
violations 2.5% risk
Vdmax


GASESE:LOAD PROFILE (20min)
0.035
0.03
0.025
0.02
0.015
0.01
0.005
0
µ/c
1-Aug
2-Aug
3-Aug
4-Aug
5-Aug
6-Aug
7-Aug
8-Aug
9-Aug
10-Aug
violations 0.1% risk
Vdmax

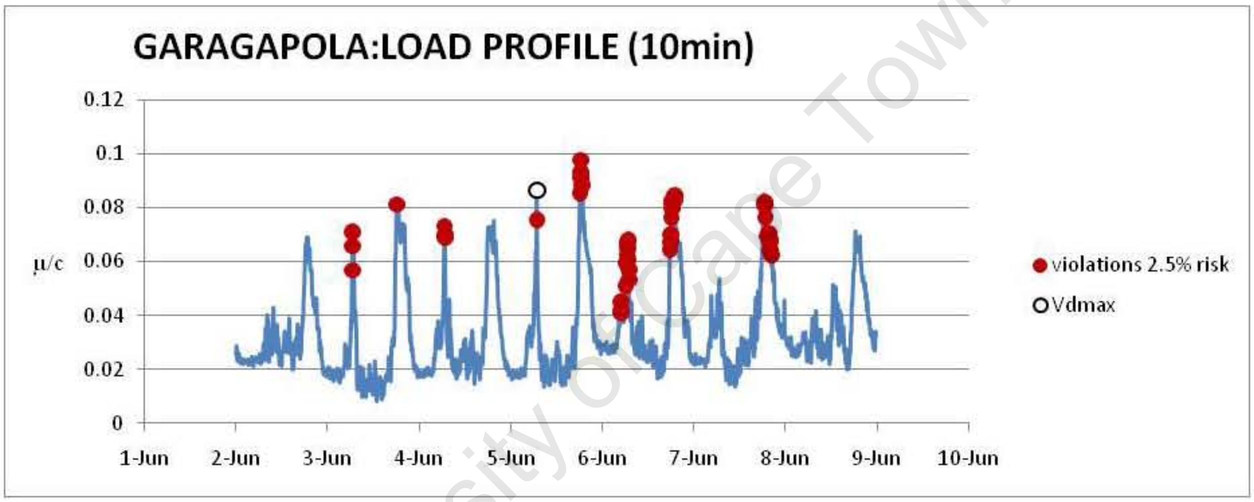

GASESE:LOAD PROFILE (20min)
0.035
0.03
0.025
0.02
0.015
0.01
0.005
0
μ/c
1-Aug
2-Aug
3-Aug
4-Aug
5-Aug
6-Aug
7-Aug
8-Aug
9-Aug
10-Aug
violations 2.5% risk
Vdmax


GARAGAPOLA:LOAD PROFILE (5min)
0.12
0.1
0.08
0.06
0.04
0.02
0
μ/c
1-Jun
2-Jun
3-Jun
4-Jun
5-Jun
6-Jun
7-Jun
8-Jun
9-Jun
10-Jun
violations 0.1% risk
Vdmax

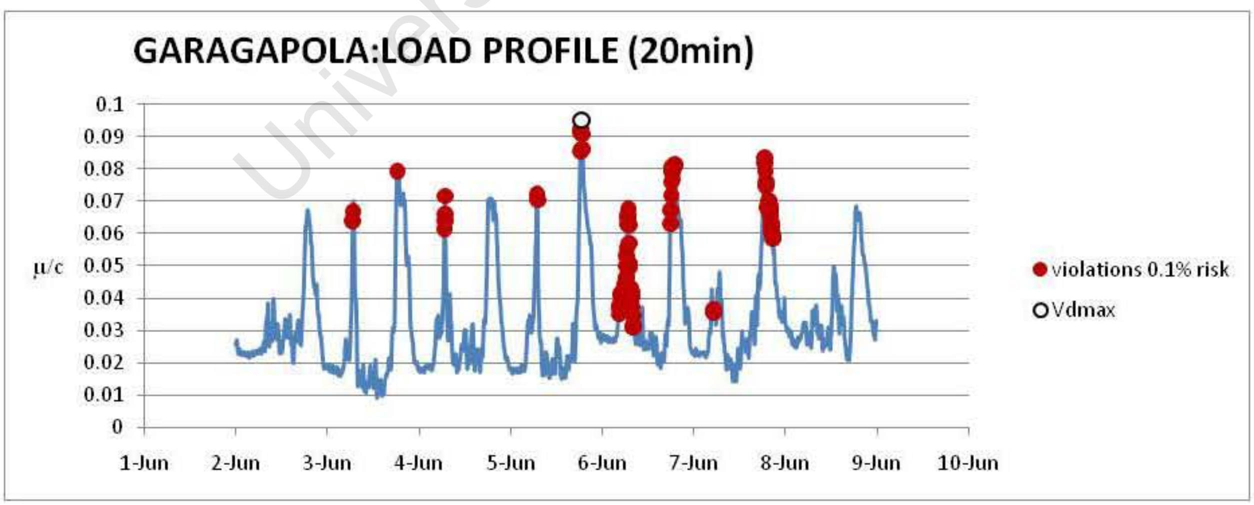

GARAGAPOLA:LOAD PROFILE (5min)
0.12
0.1
0.08
0.06
0.04
0.02
0
μ/c
1-Jun
2-Jun
3-Jun
4-Jun
5-Jun
6-Jun
7-Jun
8-Jun
9-Jun
10-Jun
violations 2.5% risk
Vdmax



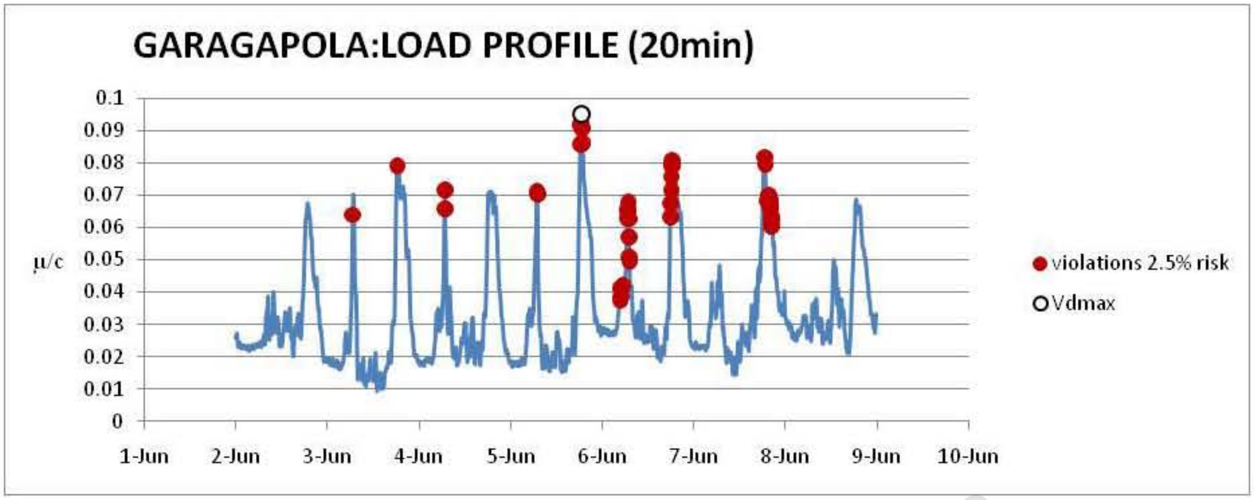
GARAGAPOLA:LOAD PROFILE (10min)
0.12
0.1
0.08
0.06
0.04
0.02
0
μ/c
1-Jun
2-Jun
3-Jun
4-Jun
5-Jun
6-Jun
7-Jun
8-Jun
9-Jun
10-Jun
violations 0.1% risk
Vdmax

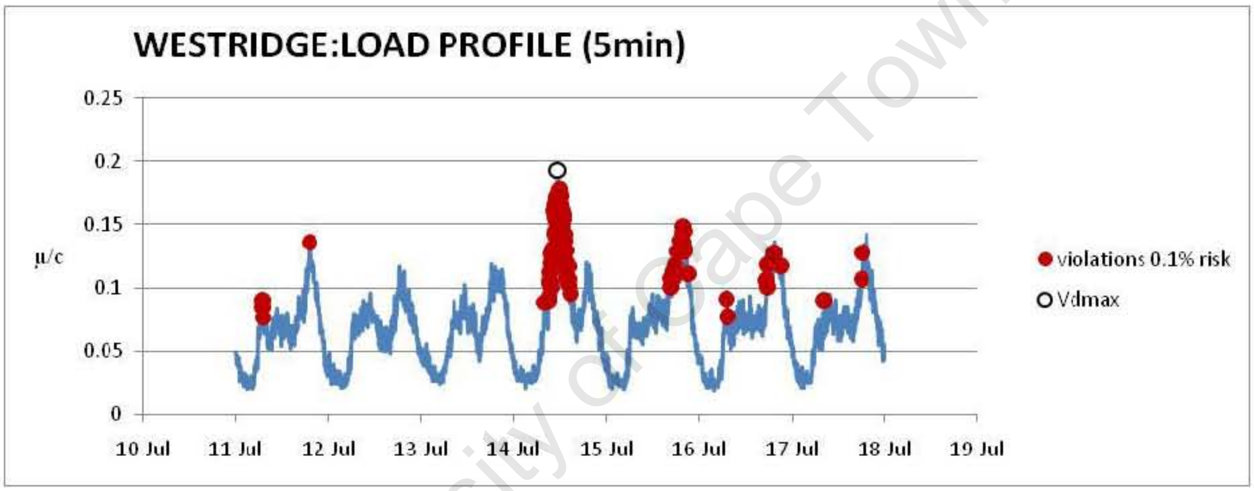


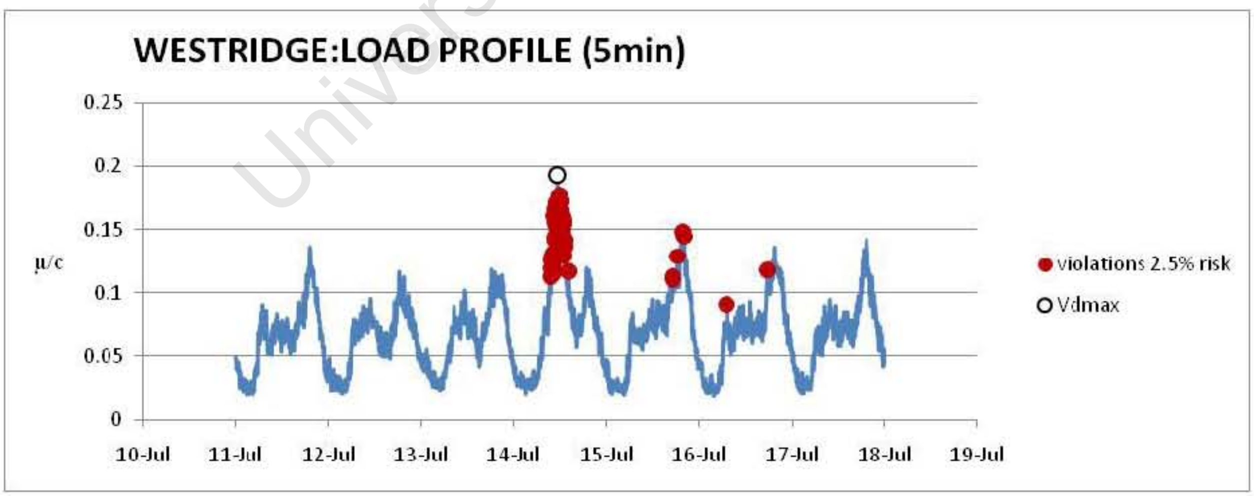
GARAGAPOLA:LOAD PROFILE (10min)
0.12
0.1
0.08
0.06
0.04
0.02
0
μ/c
1-Jun
2-Jun
3-Jun
4-Jun
5-Jun
6-Jun
7-Jun
8-Jun
9-Jun
10-Jun
violations 2.5% risk
Vdmax

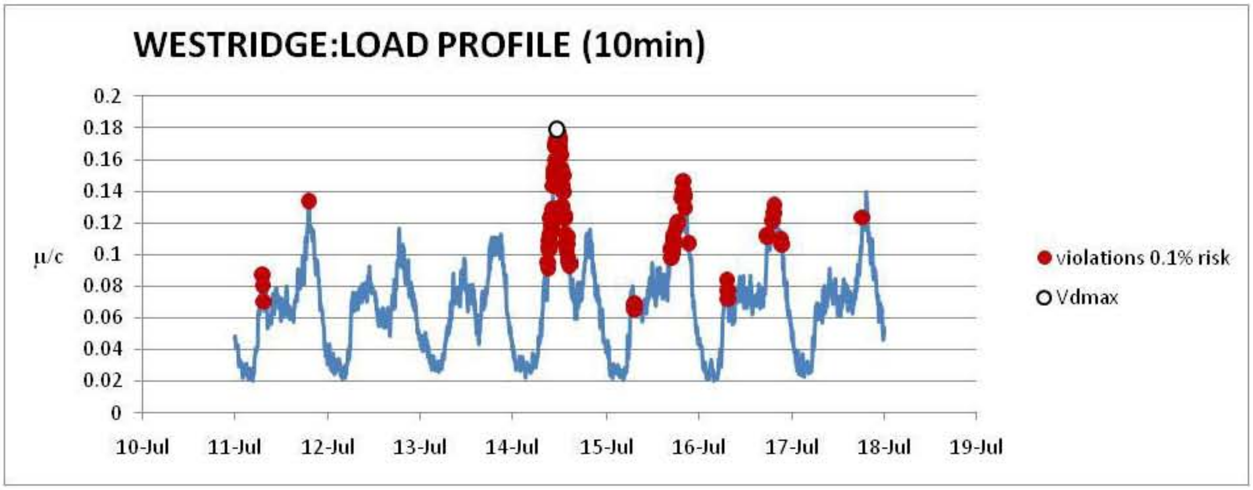


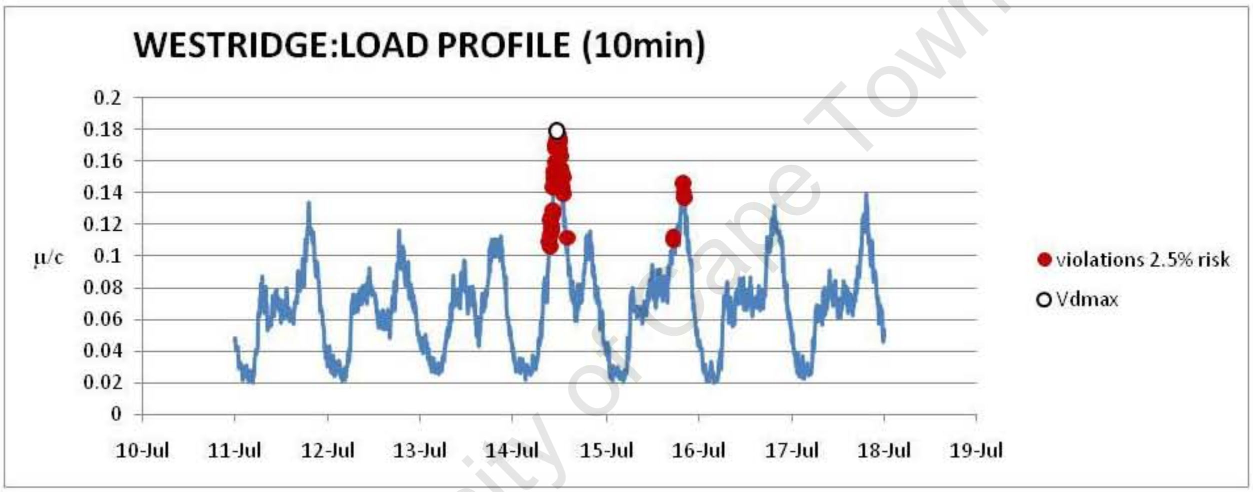
GARAGAPOLA:LOAD PROFILE (20min)
0.1
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
μ/c
1-Jun
2-Jun
3-Jun
4-Jun
5-Jun
6-Jun
7-Jun
8-Jun
9-Jun
10-Jun
violations 0.1% risk
Vdmax

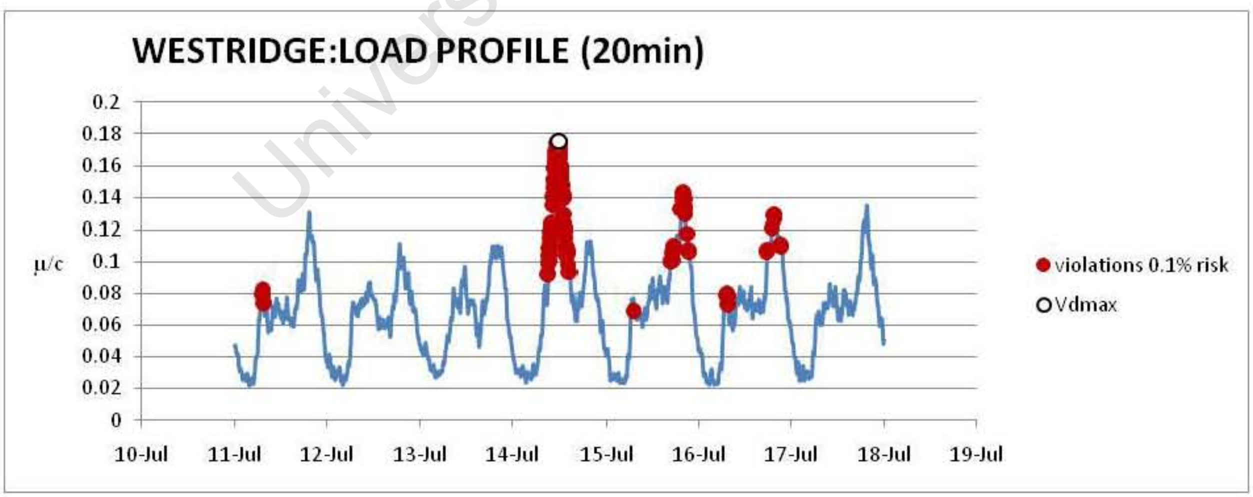

GARAGAPOLA:LOAD PROFILE (20min)
μ/c
0.1
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
1-Jun
2-Jun
3-Jun
4-Jun
5-Jun
6-Jun
7-Jun
8-Jun
9-Jun
10-Jun
violations 2.5% risk
Vdmax

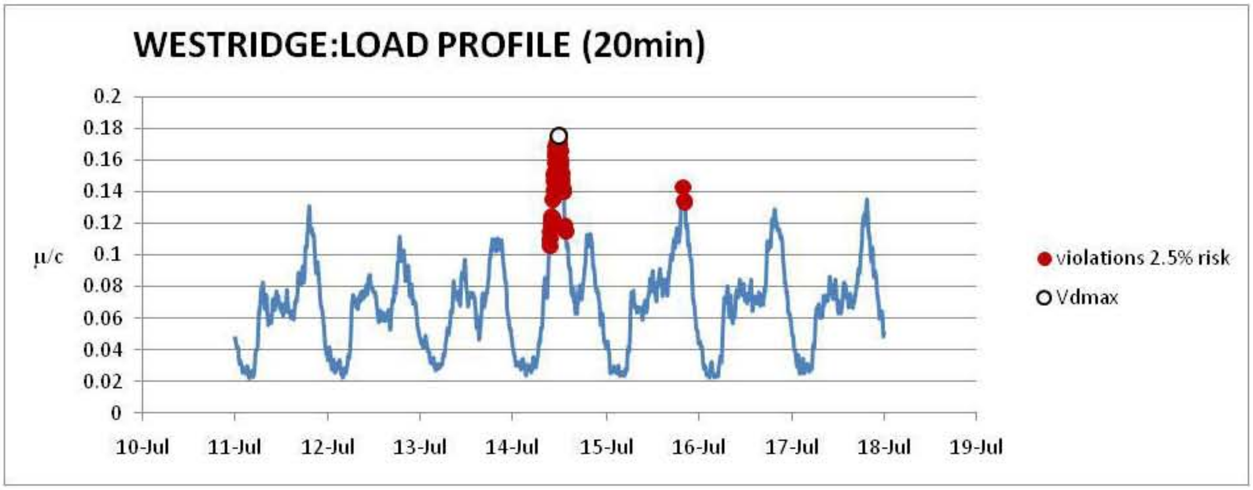

WESTRIDGE:LOAD PROFILE (5min)
μ/c
0.25
0.2
0.15
0.1
0.05
0
10 Jul
11 Jul
12 Jul
13 Jul
14 Jul
15 Jul
16 Jul
17 Jul
18 Jul
19 Jul
violations 0.1% risk
Vdmax

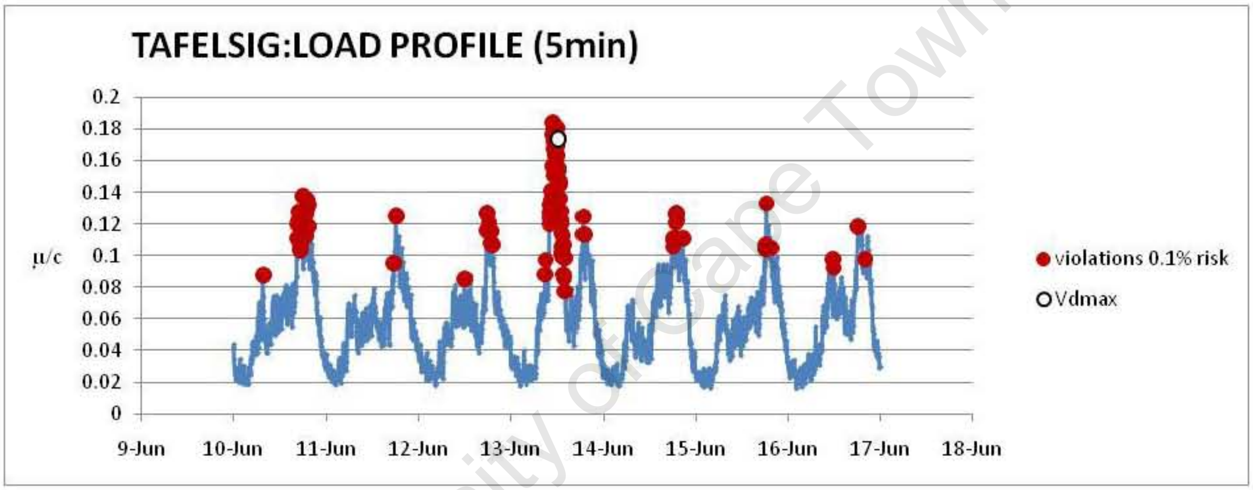

WESTRIDGE:LOAD PROFILE (5min)
μ/c
0.25
0.2
0.15
0.1
0.05
0
10-Jul
11-Jul
12-Jul
13-Jul
14-Jul
15-Jul
16-Jul
17-Jul
18-Jul
19-Jul
violations 2.5% risk
Vdmax

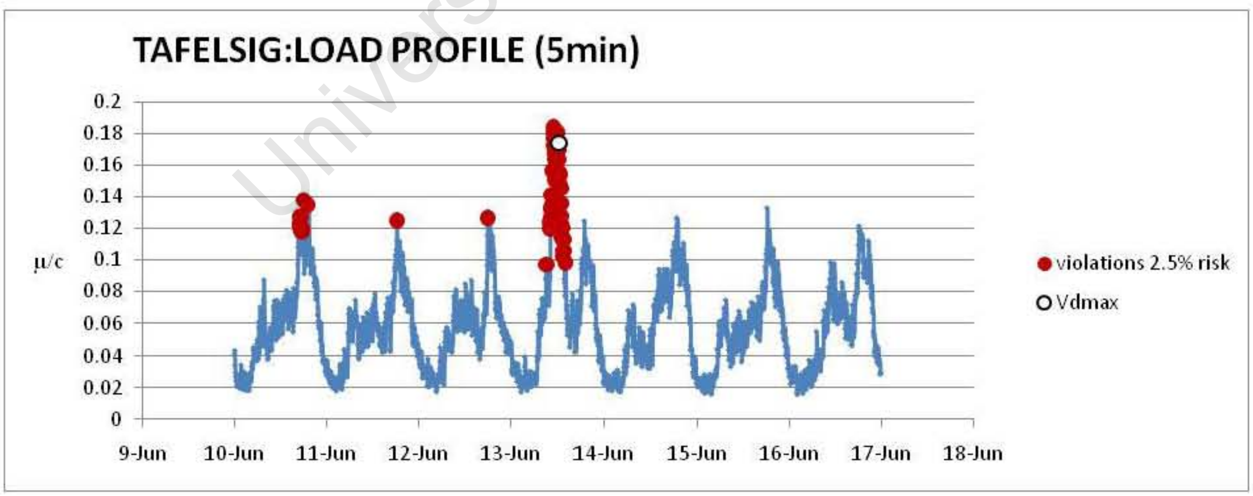

WESTRIDGE:LOAD PROFILE (10min)
µ/c
0.2
0.18
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
10-Jul
11-Jul
12-Jul
13-Jul
14-Jul
15-Jul
16-Jul
17-Jul
18-Jul
19-Jul
violations 0.1% risk
Vdmax

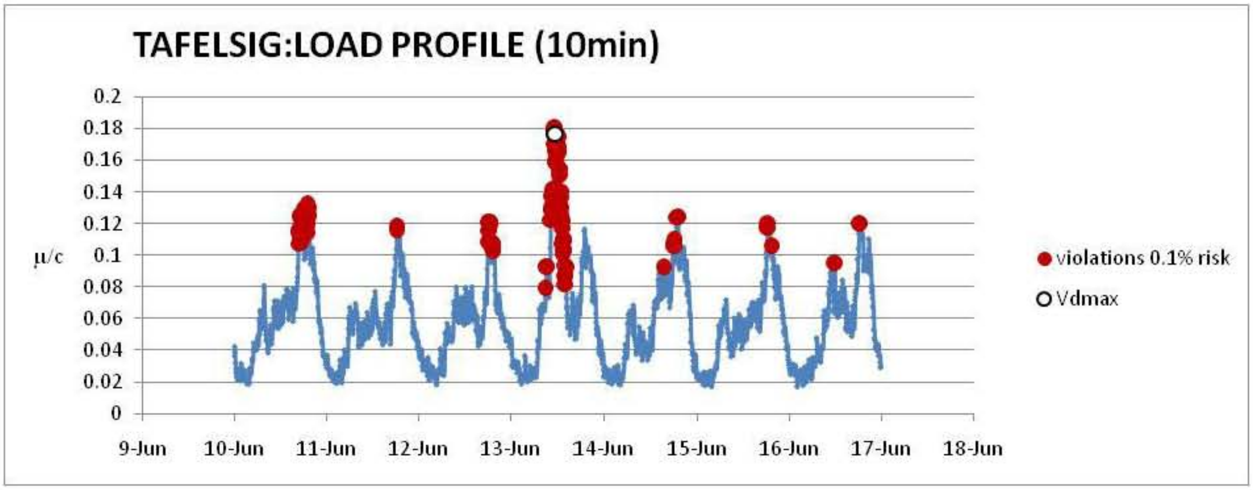

WESTRIDGE:LOAD PROFILE (10min)
µ/c
0.2
0.18
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
10-Jul
11-Jul
12-Jul
13-Jul
14-Jul
15-Jul
16-Jul
17-Jul
18-Jul
19-Jul
violations 2.5% risk
Vdmax

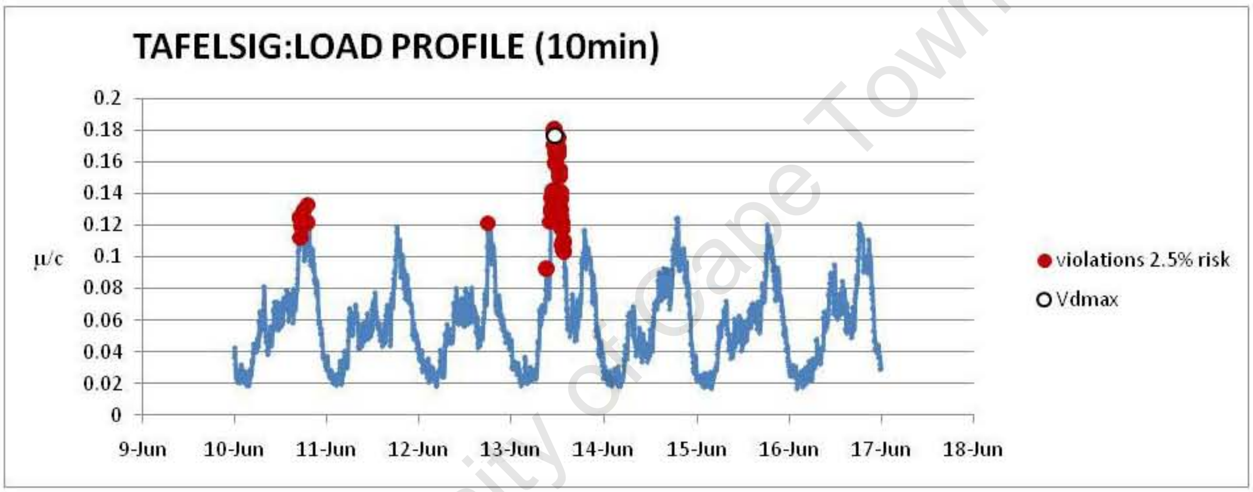

WESTRIDGE:LOAD PROFILE (20min)
µ/c
0.2
0.18
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
10-Jul
11-Jul
12-Jul
13-Jul
14-Jul
15-Jul
16-Jul
17-Jul
18-Jul
19-Jul
violations 0.1% risk
Vdmax

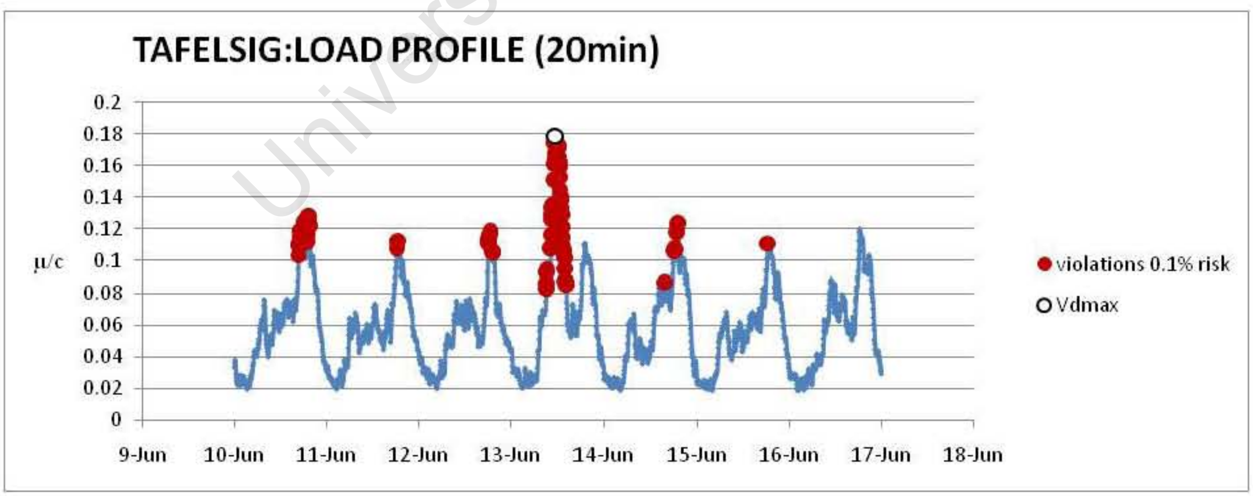

WESTRIDGE:LOAD PROFILE (20min)
μ/c
0.2
0.18
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
10-Jul
11-Jul
12-Jul
13-Jul
14-Jul
15-Jul
16-Jul
17-Jul
18-Jul
19-Jul
violations 2.5% risk
Vdmax

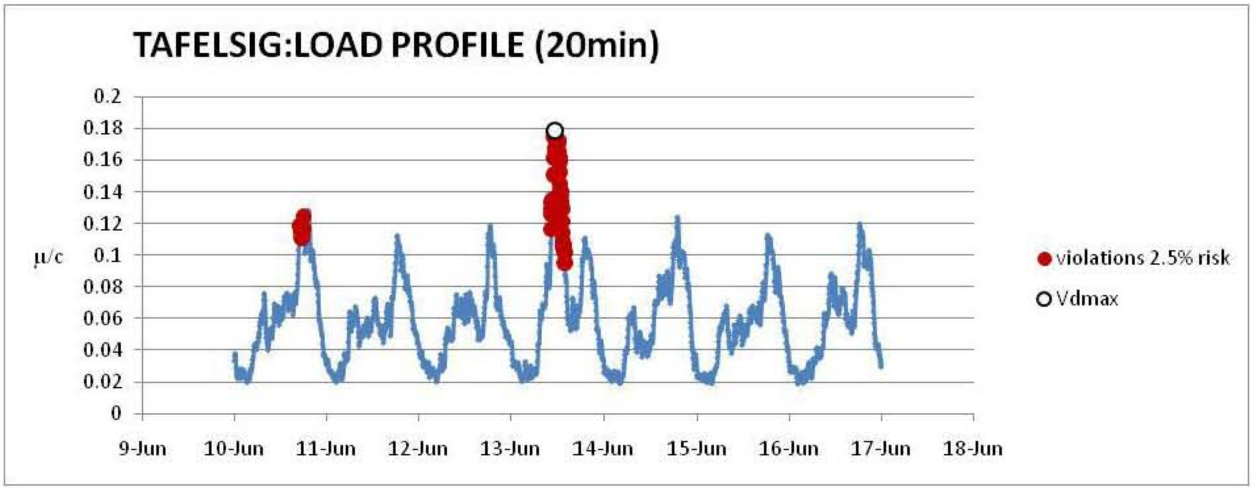

TAFELSIG:LOAD PROFILE (5min)
μ/c
0.2
0.18
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
9-Jun
10-Jun
11-Jun
12-Jun
13-Jun
14-Jun
15-Jun
16-Jun
17-Jun
18-Jun
violations 0.1% risk
Vdmax

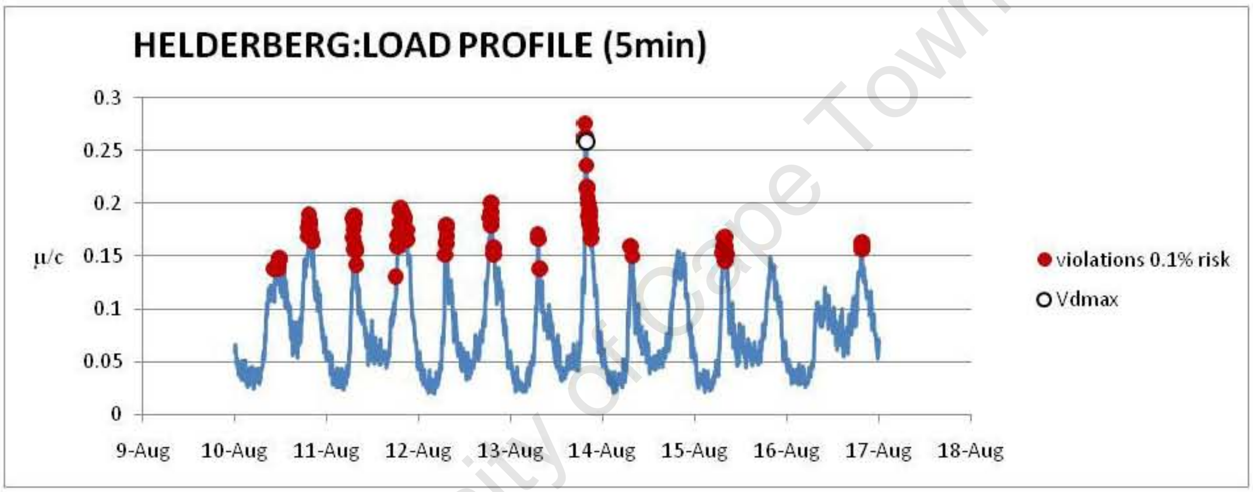

TAFELSIG:LOAD PROFILE (5min)
μ/c
0.2
0.18
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
9-Jun
10-Jun
11-Jun
12-Jun
13-Jun
14-Jun
15-Jun
16-Jun
17-Jun
18-Jun
violations 2.5% risk
Vdmax

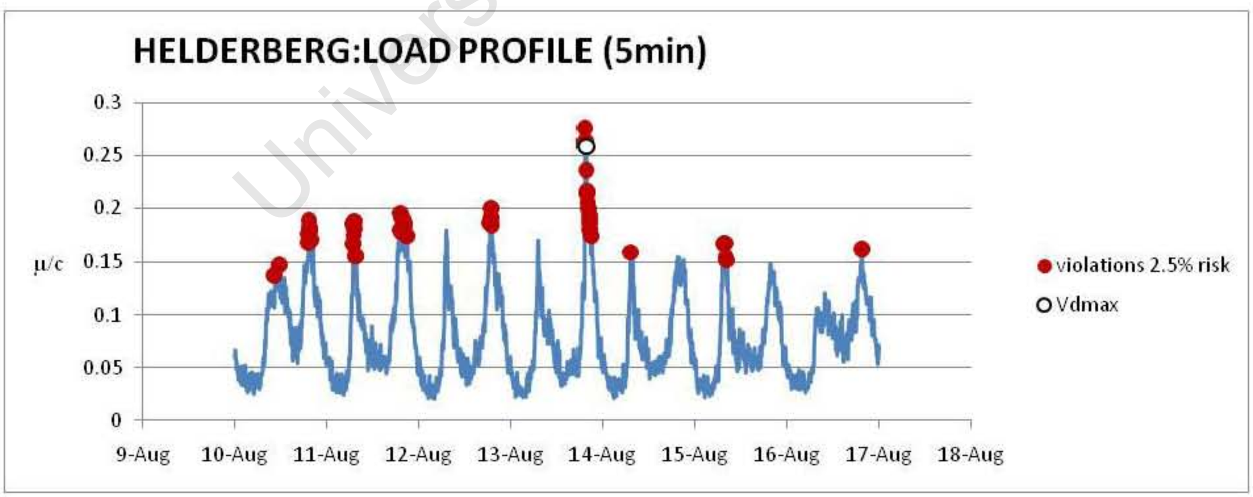

TAFELSIG:LOAD PROFILE (10min)
0.2
0.18
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
μ/c
9-Jun
10-Jun
11-Jun
12-Jun
13-Jun
14-Jun
15-Jun
16-Jun
17-Jun
18-Jun
violations 0.1% risk
Vdmax

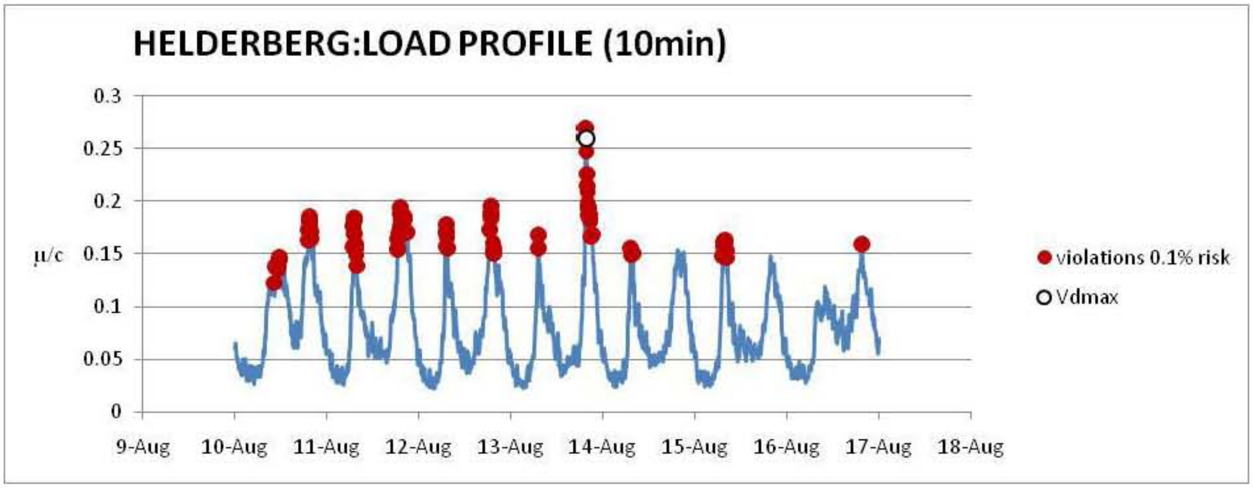

TAFELSIG:LOAD PROFILE (10min)
0.2
0.18
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
μ/c
9-Jun
10-Jun
11-Jun
12-Jun
13-Jun
14-Jun
15-Jun
16-Jun
17-Jun
18-Jun
violations 2.5% risk
Vdmax

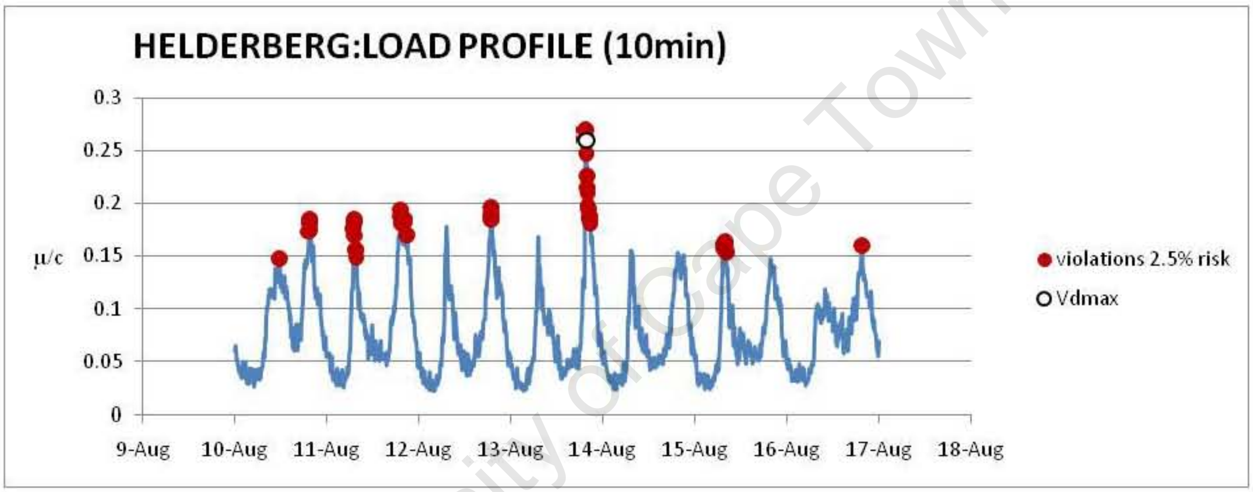

TAFELSIG:LOAD PROFILE (20min)
0.2
0.18
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
μ/c
9-Jun
10-Jun
11-Jun
12-Jun
13-Jun
14-Jun
15-Jun
16-Jun
17-Jun
18-Jun
violations 0.1% risk
Vdmax

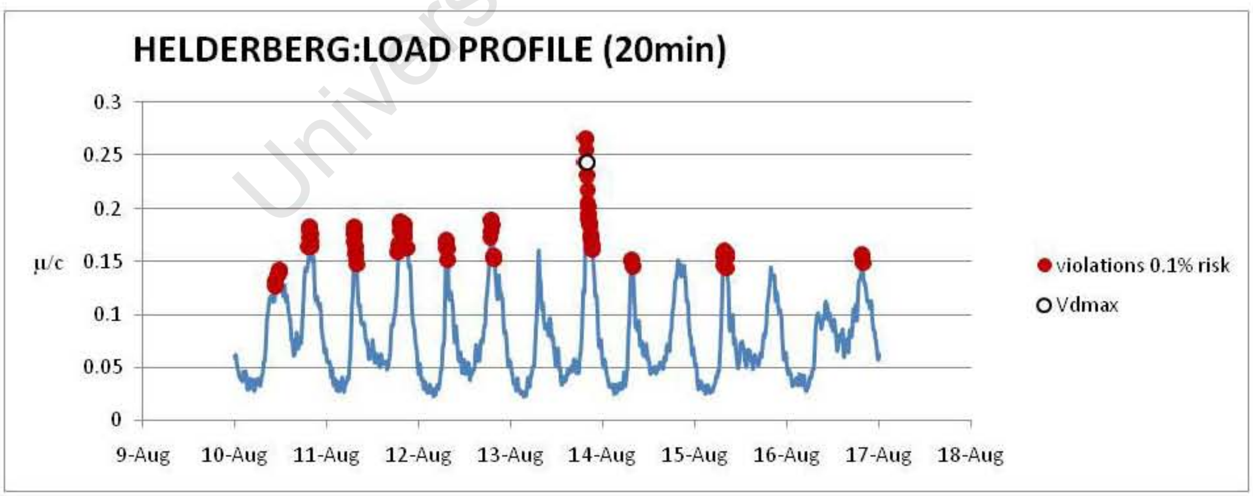

TAFELSIG:LOAD PROFILE (20min)
0.2
0.18
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
μ/c
9-Jun
10-Jun
11-Jun
12-Jun
13-Jun
14-Jun
15-Jun
16-Jun
17-Jun
18-Jun
violations 2.5% risk
Vdmax

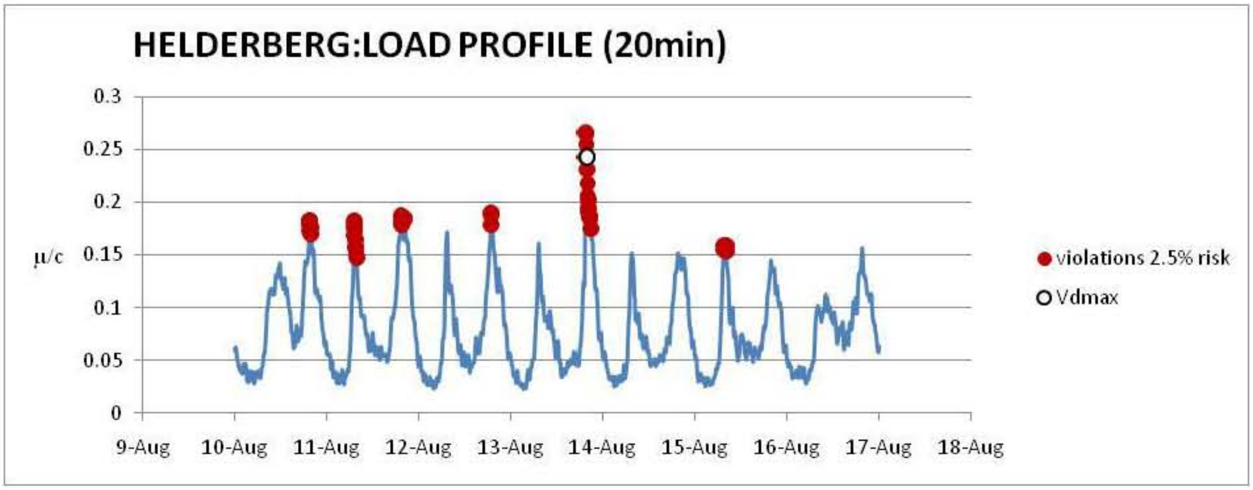

HELDERBERG:LOAD PROFILE (5min)
0.3
0.25
0.2
0.15
0.1
0.05
0
μ/c
9-Aug
10-Aug
11-Aug
12-Aug
13-Aug
14-Aug
15-Aug
16-Aug
17-Aug
18-Aug
violations 0.1% risk
Vdmax

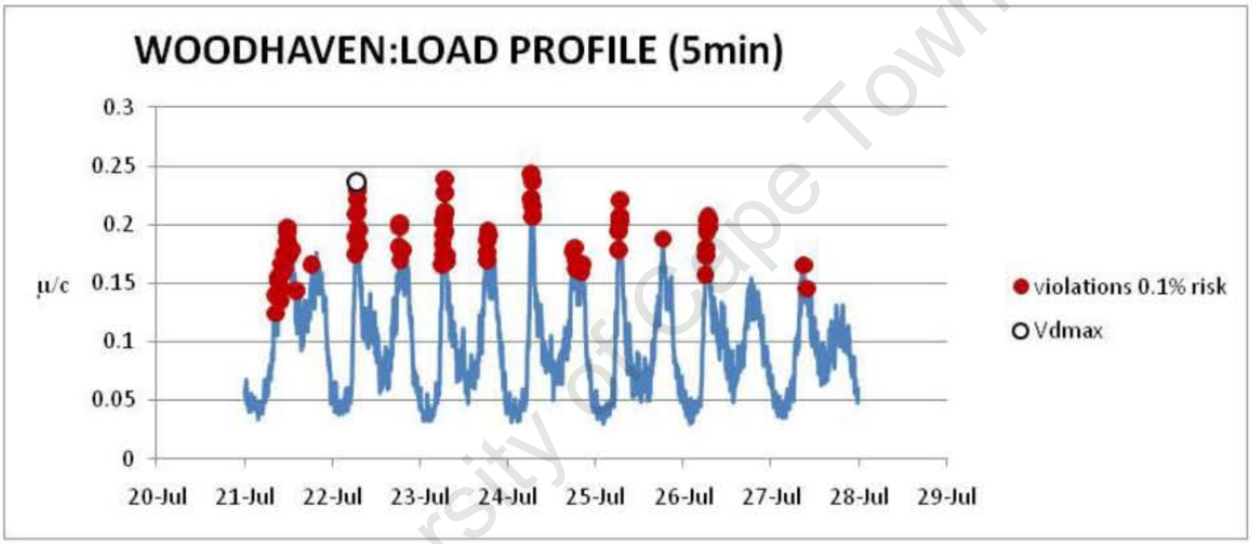

HELDERBERG:LOAD PROFILE (5min)
0.3
0.25
0.2
0.15
0.1
0.05
0
μ/c
9-Aug
10-Aug
11-Aug
12-Aug
13-Aug
14-Aug
15-Aug
16-Aug
17-Aug
18-Aug
violations 2.5% risk
Vdmax

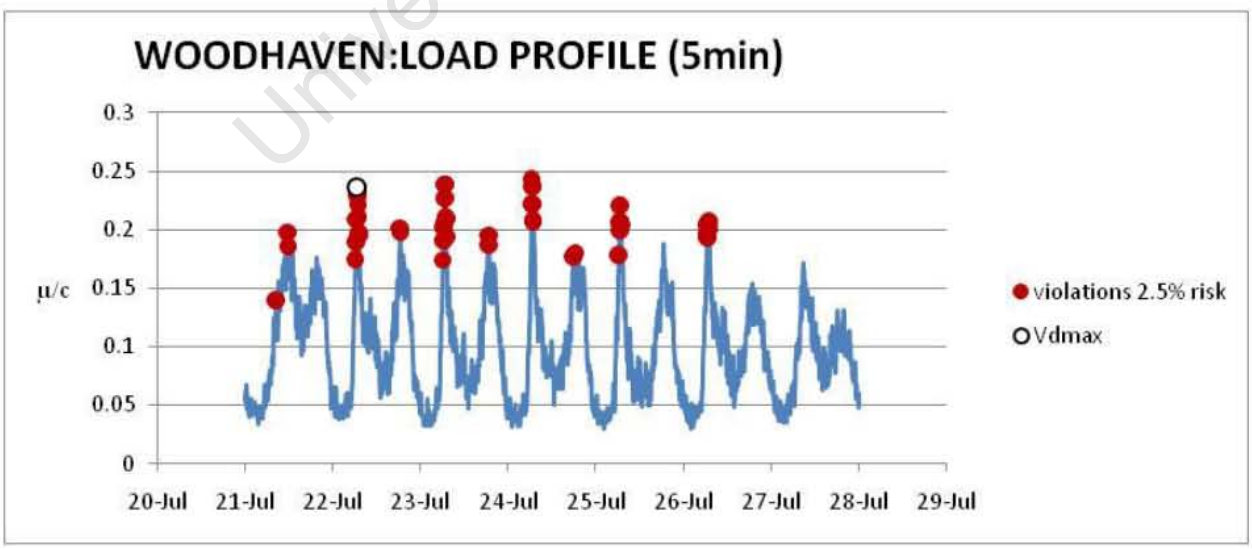

HELDERBERG:LOAD PROFILE (10min)
μ/c
0.3
0.25
0.2
0.15
0.1
0.05
0
9-Aug
10-Aug
11-Aug
12-Aug
13-Aug
14-Aug
15-Aug
16-Aug
17-Aug
18-Aug
violations 0.1% risk
Vdmax

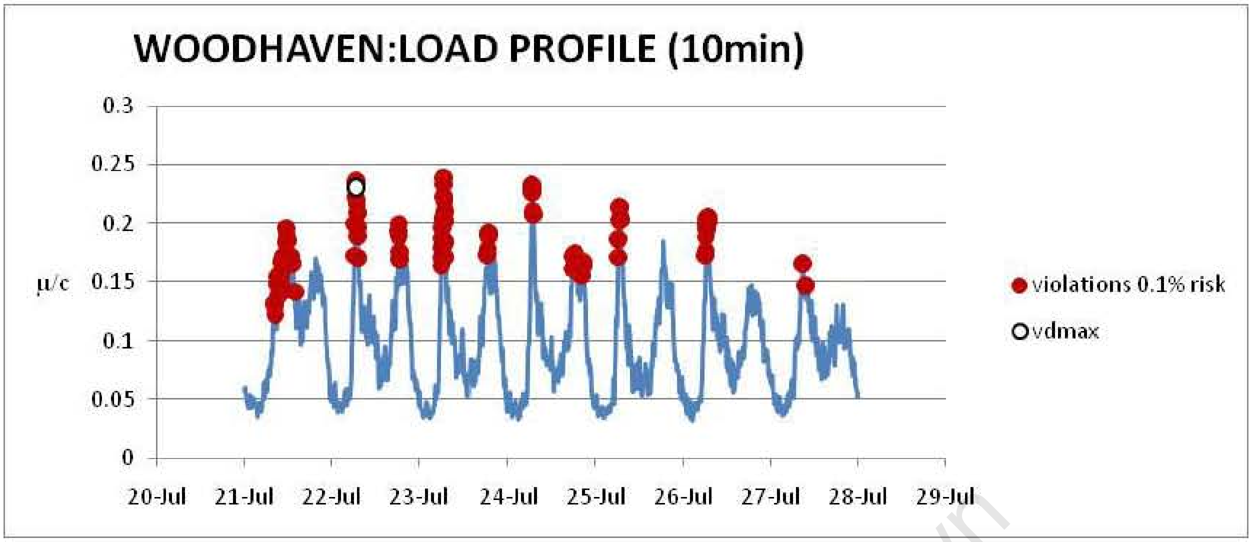

HELDERBERG:LOAD PROFILE (10min)
μ/c
0.3
0.25
0.2
0.15
0.1
0.05
0
9-Aug
10-Aug
11-Aug
12-Aug
13-Aug
14-Aug
15-Aug
16-Aug
17-Aug
18-Aug
violations 2.5% risk
Vdmax

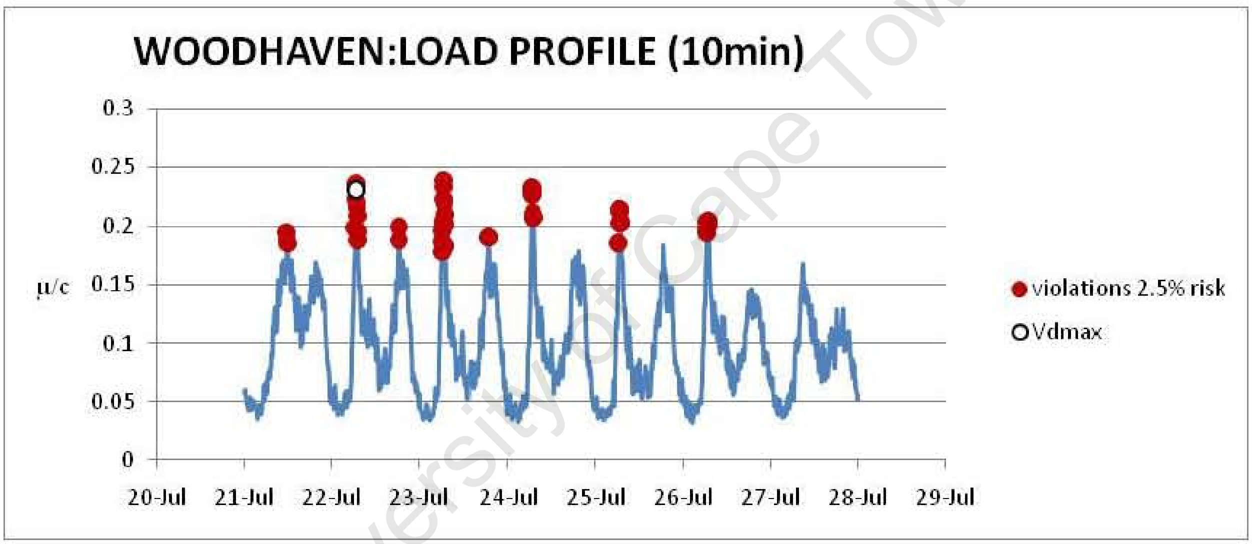

HELDERBERG:LOAD PROFILE (20min)
μ/c
0.3
0.25
0.2
0.15
0.1
0.05
0
9-Aug
10-Aug
11-Aug
12-Aug
13-Aug
14-Aug
15-Aug
16-Aug
17-Aug
18-Aug
violations 0.1% risk
Vdmax

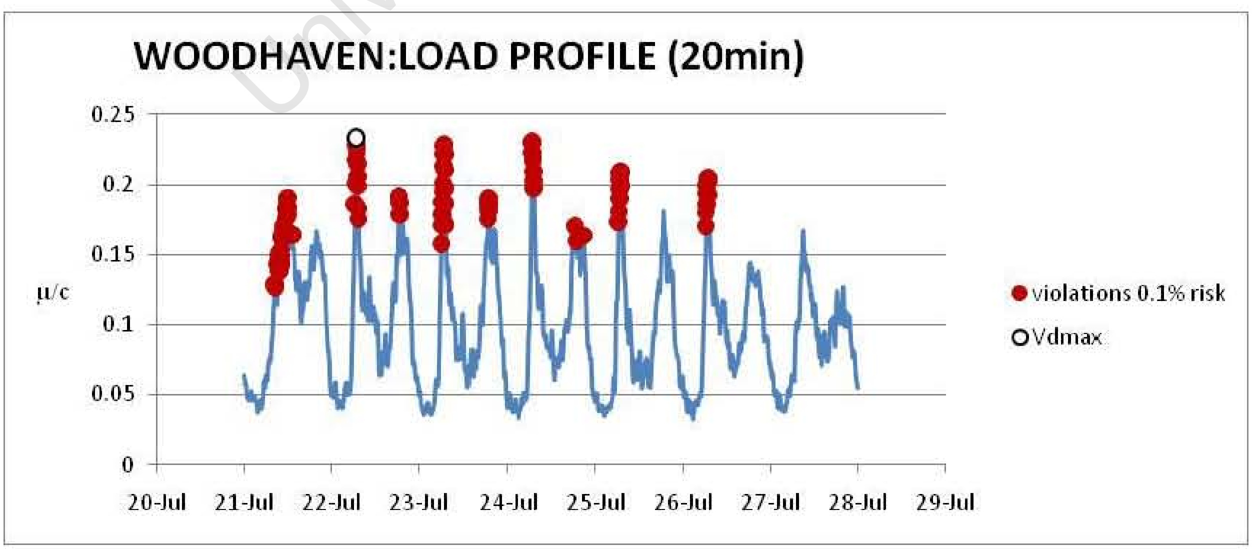

HELDERBERG:LOAD PROFILE (20min)
μ/c
0.3
0.25
0.2
0.15
0.1
0.05
0
9-Aug
10-Aug
11-Aug
12-Aug
13-Aug
14-Aug
15-Aug
16-Aug
17-Aug
18-Aug
violations 2.5% risk
Vdmax


WOODHAVEN:LOAD PROFILE (5min)
μ/c
0.3
0.25
0.2
0.15
0.1
0.05
0
20-Jul
21-Jul
22-Jul
23-Jul
24-Jul
25-Jul
26-Jul
27-Jul
28-Jul
29-Jul
violations 0.1% risk
Vdmax


WOODHAVEN:LOAD PROFILE (5min)
μ/c
0.3
0.25
0.2
0.15
0.1
0.05
0
20-Jul
21-Jul
22-Jul
23-Jul
24-Jul
25-Jul
26-Jul
27-Jul
28-Jul
29-Jul
violations 2.5% risk
Vdmax


WOODHAVEN:LOAD PROFILE (10min)
0.3
0.25
0.2
0.15
0.1
0.05
0
μ/c
20-Jul
21-Jul
22-Jul
23-Jul
24-Jul
25-Jul
26-Jul
27-Jul
28-Jul
29-Jul
violations 0.1% risk
vdmax


WOODHAVEN:LOAD PROFILE (10min)
0.3
0.25
0.2
0.15
0.1
0.05
0
μ/c
20-Jul
21-Jul
22-Jul
23-Jul
24-Jul
25-Jul
26-Jul
27-Jul
28-Jul
29-Jul
violations 2.5% risk
Vdmax


WOODHAVEN:LOAD PROFILE (20min)
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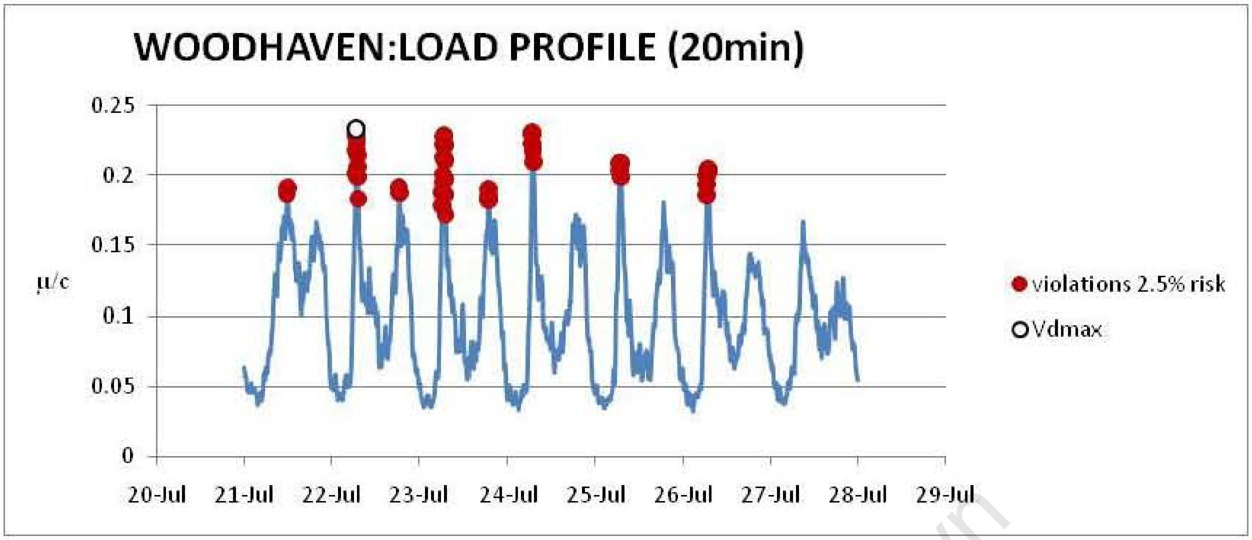
0.2
0.15
0.1
0.05
0
μ/c
20-Jul
21-Jul
22-Jul
23-Jul
24-Jul
25-Jul
26-Jul
27-Jul
28-Jul
29-Jul
violations 0.1% risk
Vdmax


WOODHAVEN:LOAD PROFILE (20min)
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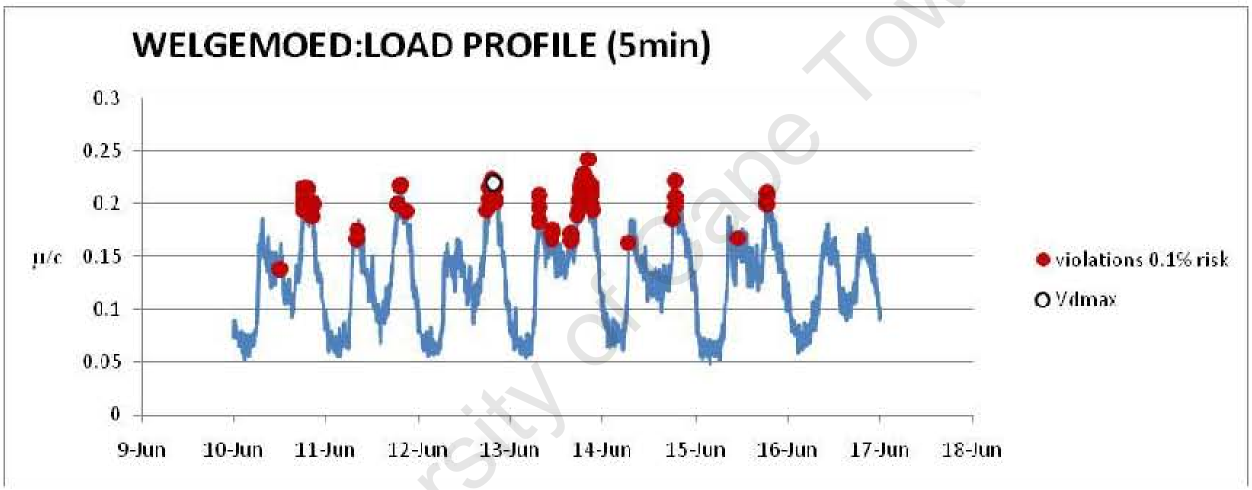
0.2
0.15
0.1
0.05
0
µ/c
20-Jul
21-Jul
22-Jul
23-Jul
24-Jul
25-Jul
26-Jul
27-Jul
28-Jul
29-Jul
violations 2.5% risk
Vdmax


WELGEMOED:LOAD PROFILE (5min)
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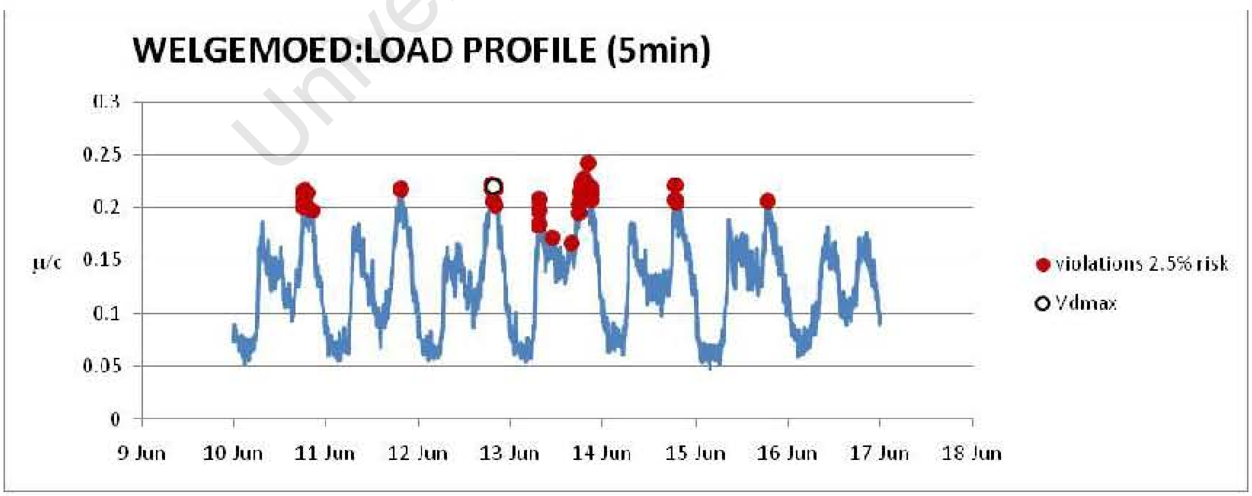
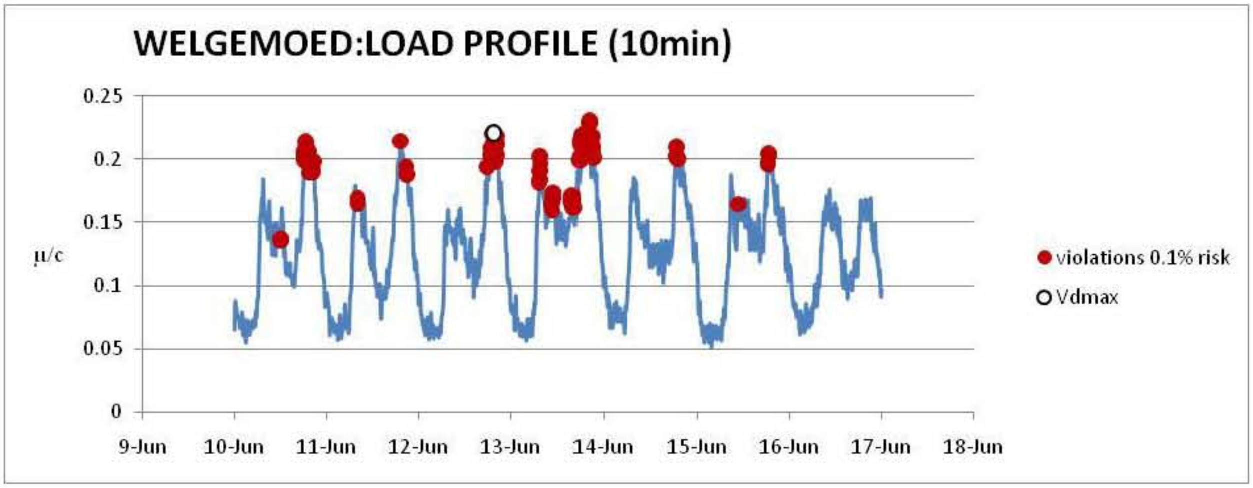
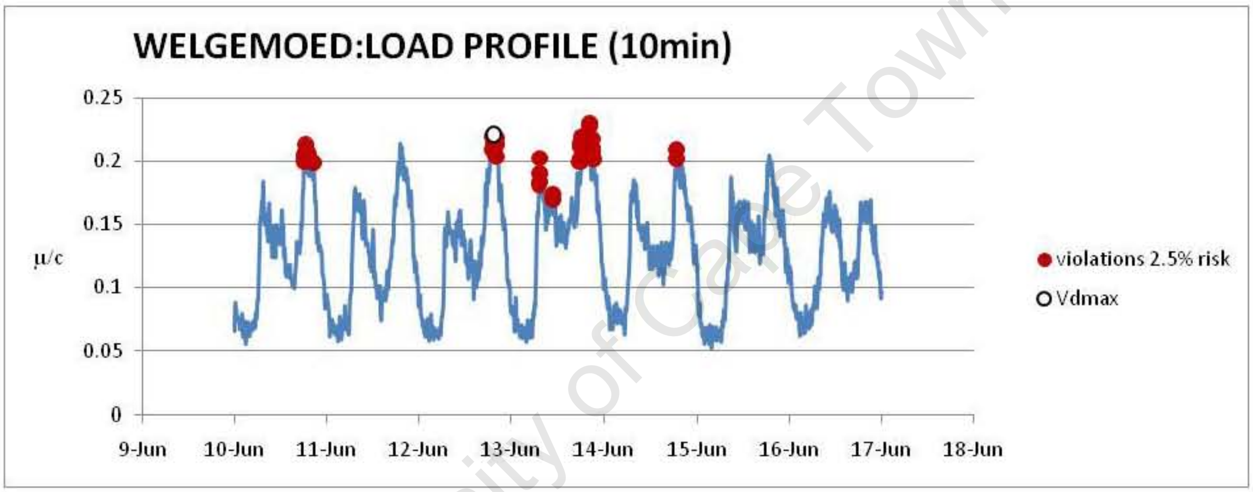
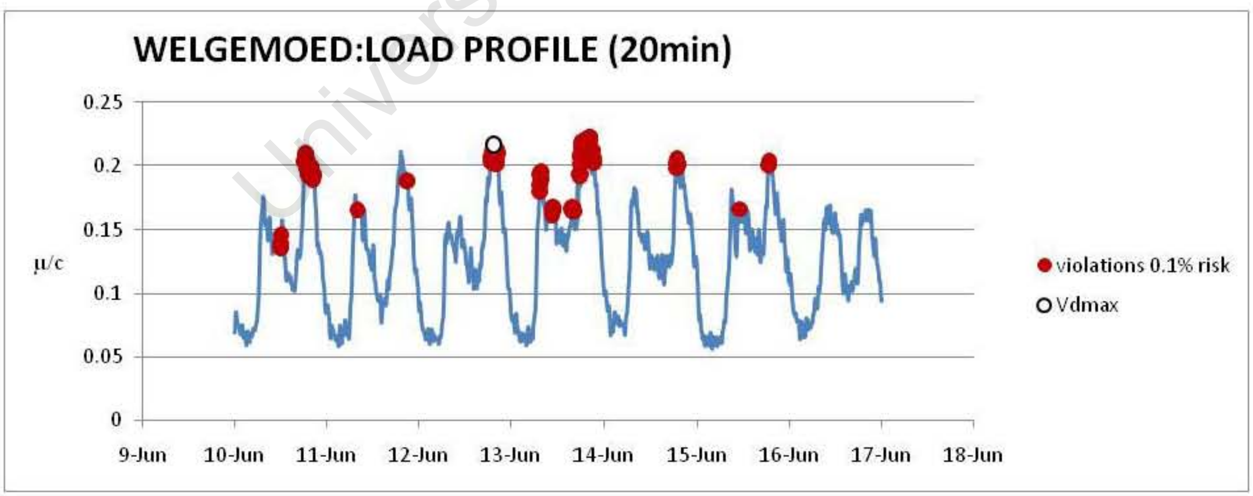
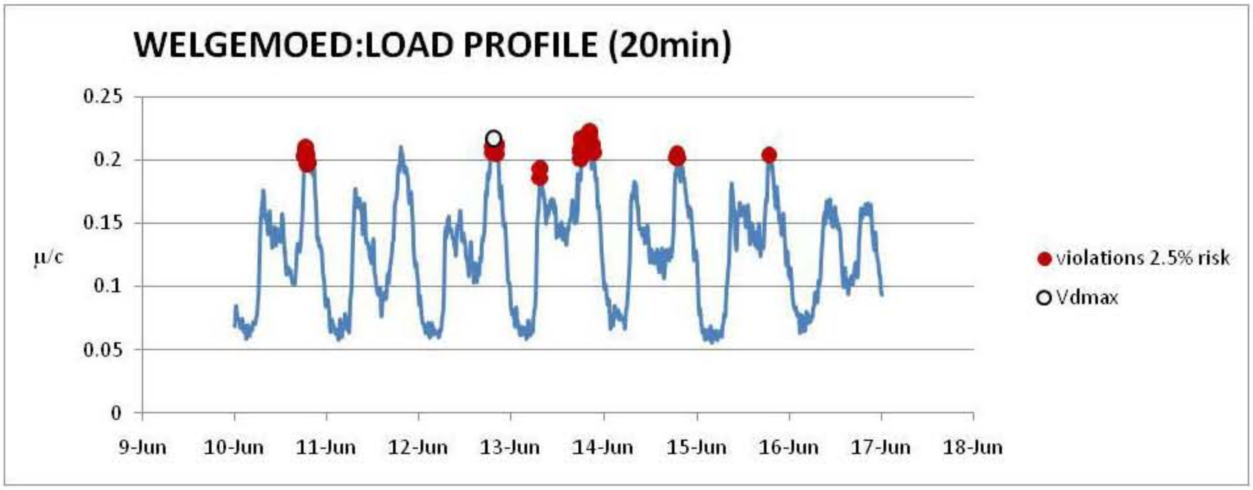
0.25
0.2
0.15
0.1
0.05
0
µ/c
9-Jun
10-Jun
11-Jun
12-Jun
13-Jun
14-Jun
15-Jun
16-Jun
17-Jun
18-Jun
violations 0.1% risk
Vdmax

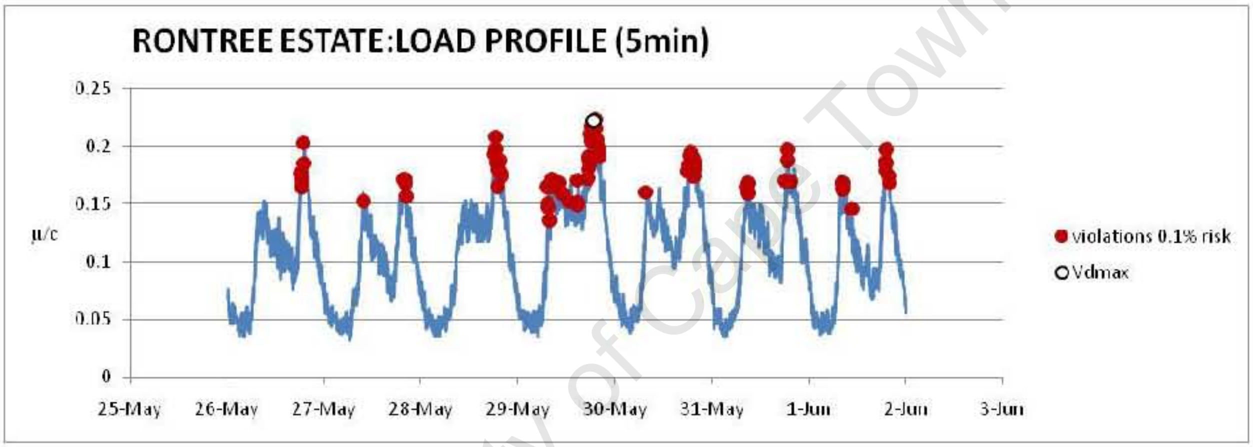

WELGEMOED:LOAD PROFILE (5min)
0.3
0.25
0.2
0.15
0.1
0.05
0
µ/c
9 Jun
10 Jun
11 Jun
12 Jun
13 Jun
14 Jun
15 Jun
16 Jun
17 Jun
18 Jun
violations 2.5% risk
Vdmax

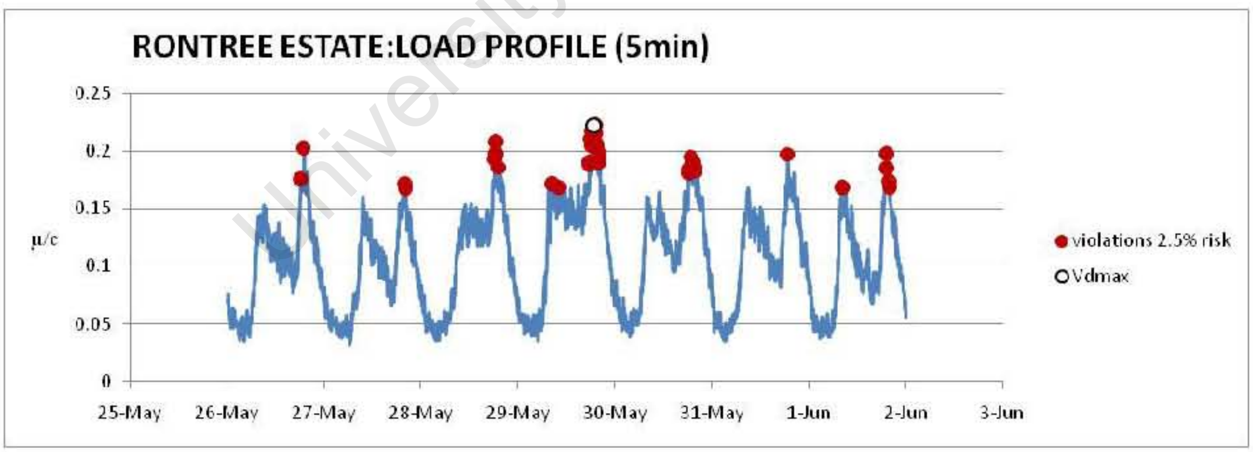

WELGEMOED:LOAD PROFILE (10min)
μ/c
0.25
0.2
0.15
0.1
0.05
0
9-Jun
10-Jun
11-Jun
12-Jun
13-Jun
14-Jun
15-Jun
16-Jun
17-Jun
18-Jun
violations 0.1% risk
Vdmax

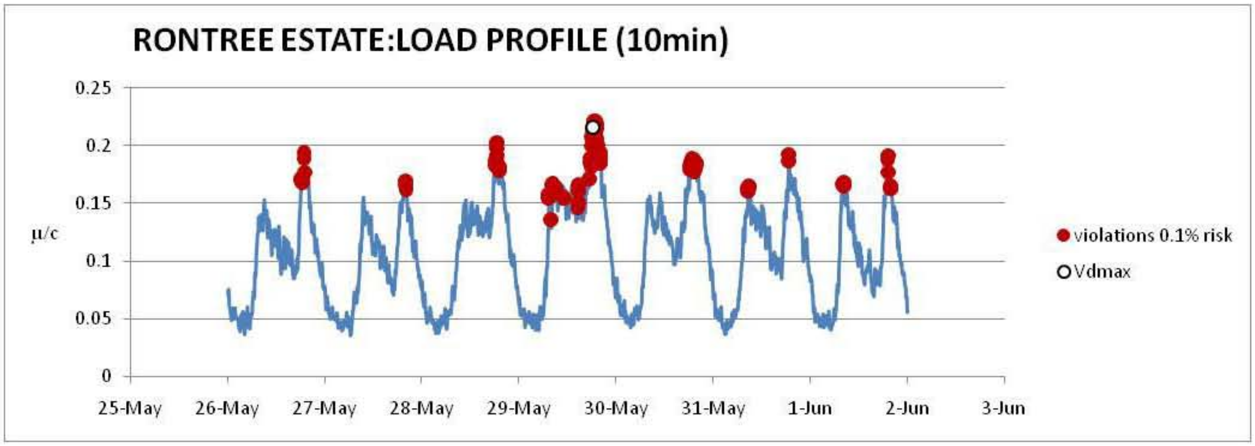

WELGEMOED:LOAD PROFILE (10min)
μ/c
0.25
0.2
0.15
0.1
0.05
0
9-Jun
10-Jun
11-Jun
12-Jun
13-Jun
14-Jun
15-Jun
16-Jun
17-Jun
18-Jun
violations 2.5% risk
Vdmax

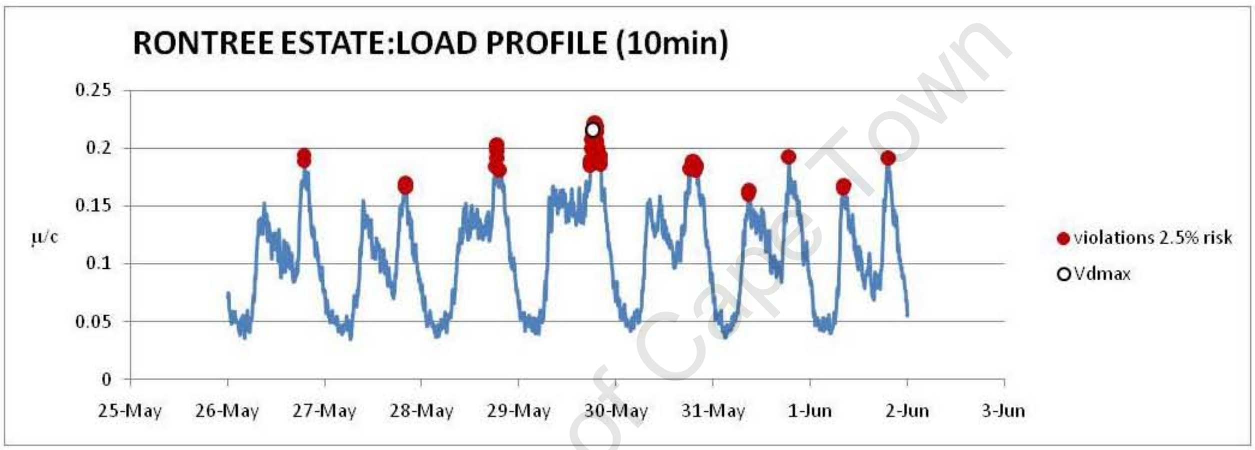

WELGEMOED:LOAD PROFILE (20min)
μ/c
0.25
0.2
0.15
0.1
0.05
0
9-Jun
10-Jun
11-Jun
12-Jun
13-Jun
14-Jun
15-Jun
16-Jun
17-Jun
18-Jun
violations 0.1% risk
Vdmax

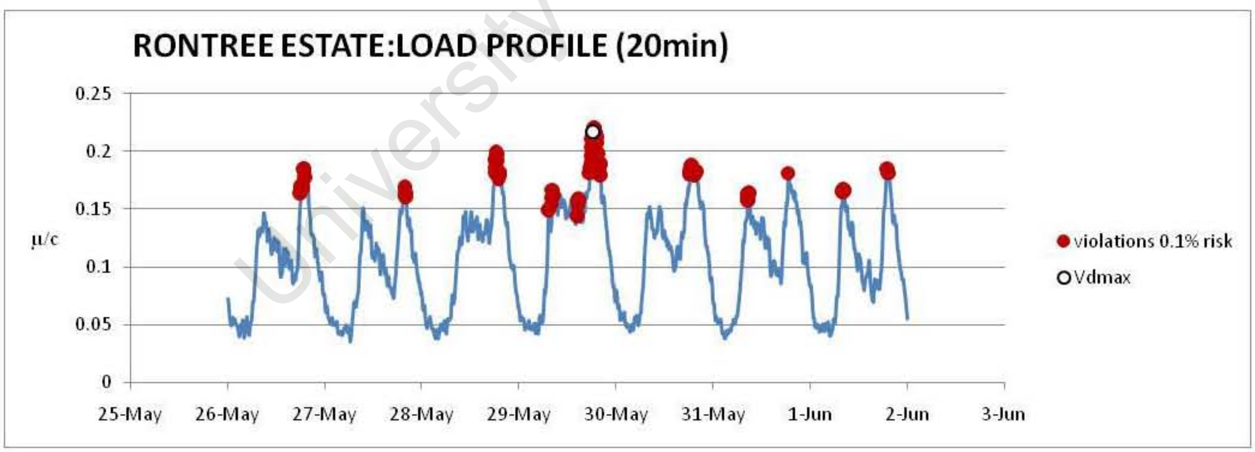

WELGEMOED:LOAD PROFILE (20min)
0.25
0.2
0.15
μ/c
0.1
0.05
0
9-Jun
10-Jun
11-Jun
12-Jun
13-Jun
14-Jun
15-Jun
16-Jun
17-Jun
18-Jun
violations 2.5% risk
Vdmax

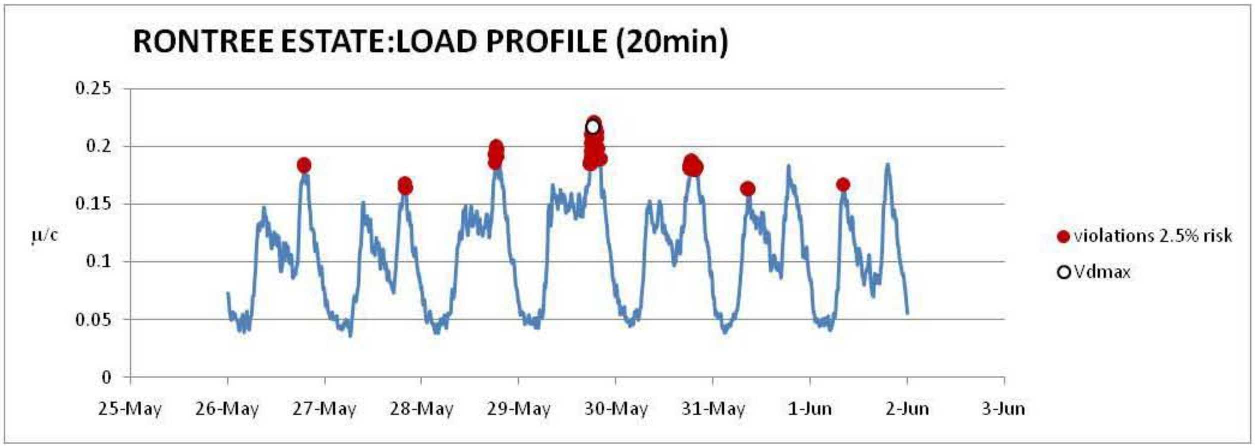

RONTREE ESTATE:LOAD PROFILE (5min)
0.25
0.2
0.15
μ/c
0.1
0.05
0
25-May
26-May
27-May
28-May
29-May
30-May
31-May
1-Jun
2-Jun
3-Jun
violations 0.1% risk
Vdmax


RONTREE ESTATE:LOAD PROFILE (5min)
0.25
0.2
0.15
μ/c
0.1
0.05
0
25-May
26-May
27-May
28-May
29-May
30-May
31-May
1-Jun
2-Jun
3-Jun
violations 2.5% risk
Vdmax


RONTREE ESTATE:LOAD PROFILE (10min)
μ/c
0.25
0.2
0.15
0.1
0.05
0
25-May
26-May
27-May
28-May
29-May
30-May
31-May
1-Jun
2-Jun
3-Jun
violations 0.1% risk
Vdmax


RONTREE ESTATE:LOAD PROFILE (10min)
μ/c
0.25
0.2
0.15
0.1
0.05
0
25-May
26-May
27-May
28-May
29-May
30-May
31-May
1-Jun
2-Jun
3-Jun
violations 2.5% risk
Vdmax


RONTREE ESTATE:LOAD PROFILE (20min)
μ/c
0.25
0.2
0.15
0.1
0.05
0
25-May
26-May
27-May
28-May
29-May
30-May
31-May
1-Jun
2-Jun
3-Jun
violations 0.1% risk
Vdmax


RONTREE ESTATE:LOAD PROFILE (20min)
0.25
0.2
0.15
0.1
0.05
0
µ/c
25-May
26-May
27-May
28-May
29-May
30-May
31-May
1-Jun
2-Jun
3-Jun
violations 2.5% risk
Vdmax

APPENDIX D

The tables showing the results derived from the investigation for all measured communities are provided in this appendix.

	Cb	SS	WW		5min	10min	20min
Moreletta Park	80.350	38-62	7/24/2001 0:00	Date(ADMD)	7/26/2001 19:10	7/27/2001 6:50	7/27/2001 7:00
2001 S			7/30/2001 23:55	M/C (ADMD)	0.300780001	0.293268109	0.28788224
				Ac	2.3178716	3.096605947	3.925878186
				Bc	5.38833091	7.462353077	9.711219363
				Date(Vdmax)	7/26/2001 18:15	7/26/2001 18:20	7/26/2001 18:20
				M/C (Vdmax)	0.266114597	0.269070175	0.266915179
				Avdmax	1.019970078	1.17745705	1.438728309
				Bvdmax	2.812852658	3.198565124	3.951479596
				Aqos(0.1%)	2.6179	2.7591	2.9298
				Aqos(0.1%)Br	2.4554	2.5841	2.7634
				Aqos(2.5%)	2.6897	2.7966	3.0009
				Aqos(2.5%)Br	2.5116	2.6216	2.8259
				Aqos(5.0%)	1.6304	1.6716	1.9821
				Aqos(5.0%)Br	1.5804	1.6279	1.9259

Summerstrand	55.559	44-52	4/29/2000 0:00	Date(ADMD)	5/2/2000 19:10	5/2/2000 19:10	5/2/2000 19:10
200F			5/5/2000 23:55	M/C (ADMD)	0.164402866	0.151851997	0.145178646
				Ac	0.599339715	0.674715764	0.719239532
				Bc	3.046215438	3.768530143	4.234929354
				Date(Vdmax)	5/2/2000 19:10	5/2/2000 18:50	5/2/2000 19:00
				M/C (Vdmax)	0.164402866	0.143134361	0.140819829
				Avdmax	0.599339715	0.556959012	0.623149525
				Bvdmax	3.046215438	3.334203156	3.802005167
				Aqos(0.1%)	1.4822	1.3982	1.4536
				Aqos(0.1%)Br	1.3806	1.3247	1.3849
				Aqos(2.5%)	1.4243	1.3763	1.4192
				Aqos(2.5%)Br	1.3087	1.281	1.3349
				Aqos(5.0%)	0.5993	0.6747	0.6942
				Aqos(5.0%)Br	0.5993	0.6747	0.6911

Sanctuary Gardens	54.373	64	7/17/1999 0:00	Date(ADMD)	7/20/1999 21:20	7/20/1999 21:25	7/20/1999 21:35
1999S			7/23/1999 23:55	M/C (ADMD)	0.212360397	0.208033226	0.200535106
				Ac	1.602612304	1.670127692	1.774834615
				Bc	5.944050461	6.358049938	7.075658711
				Date(Vdmax)	7/23/1999 7:05	7/23/1999 7:05	7/20/1999 21:35
				M/C (Vdmax)	0.1639158	0.164333487	0.200535106
				Avdmax	0.62508668	0.79027212	1.774834615
				Bvdmax	3.188375363	4.018681505	7.075658711
				Aqos(0.1%)	2.2682	2.7092	3.0248
				Aqos(0.1%)Br	2.0823	2.4451	2.7295
				Aqos(2.5%)	2.6776	3.0826	3.5119
				Aqos(2.5%)Br	2.3214	2.6826	3.0123
				Aqos(5.0%)	1.6026	1.6701	1.7748
				Aqos(5.0%)Br	1.5026	1.6701	1.7748

Woodhaven	65.215	44-49	7/21/2002 0:00	Date(ADMD)	7/24/2002 6:30	7/23/2002 6:45	7/22/2002 6:50
2002S			7/27/2002 23:55	M/C (ADMD)	0.242938663	0.23875689	0.233175822
				Ac	1.933449973	1.763764945	1.430742728
				Bc	6.025143156	5.623519005	4.705153852
				Date(Vdmax)	7/22/2002 6:35	7/22/2002 6:50	7/22/2002 6:50
				M/C (Vdmax)	0.236209586	0.230380672	0.233175822
				Avdmax	1.242802518	1.277919768	1.430742728
				Bvdmax	4.018637282	4.269072339	4.705153852
				Aqos(0.1%)	3.4647	3.8388	4.0307
				Aqos(0.1%)Br	3.1319	3.4638	3.6557
				Aqos(2.5%)	3.7334	4.0138	4.2557
				Aqos(2.5%)Br	3.2366	3.5138	3.7807
				Aqos(5.0%)	1.3959	1.4825	1.4307
				Aqos(5.0%)Br	1.3772	1.4575	1.4307

Welgemoed	78.291	53-62	6/10/2002 0:00	Date(ADMD)	6/13/2002 20:00	6/13/2002 20:05	6/13/2002 19:35
2002F			6/16/2002 23:55	M/C (ADMD)	0.242396222	0.23055086	0.223524688
				Ac	1.169901044	1.393385796	2.03108196
				Bc	3.656498617	4.650338336	7.055529379
				Date(Vdmax)	6/12/2002 19:25	6/12/2002 19:30	6/12/2002 19:25
				M/C (Vdmax)	0.219706185	0.220734833	0.216558054
				Avdmax	0.803117105	0.932397455	0.946006586
				Bvdmax	2.852297074	3.291663787	3.422367476
				Aqos(0.1%)	1.9449	1.8309	1.8139
				Aqos(0.1%)Br	1.8605	1.7653	1.7483
				Aqos(2.5%)	1.998	1.8309	1.7936
				Aqos(2.5%)Br	1.8699	1.7371	1.7311
				Aqos(5.0%)	1.1699	1.109	1.0717
				Aqos(5.0%)Br	1.1387	1.0934	1.0623

Rontree Estate	78.269	59	5/26/2000 0:00	Date(ADMD)	5/29/2000 19:15	5/29/2000 18:50	5/29/2000 18:40
2000F			6/1/2000 23:55	M/C (ADMD)	0.222918096	0.221423357	0.220008473
				Ac	1.214619205	1.506674165	1.718896903
				Bc	4.234104917	5.297821023	6.093969922
				Date(Vdmax)	5/29/2000 18:50	5/29/2000 18:20	5/29/2000 18:20
				M/C (Vdmax)	0.222128986	0.215735345	0.217038869
				Avdmax	1.154619125	1.258649681	1.476000963
				Bvdmax	4.043347819	4.57558058	5.324628663
				Aqos(0.1%)	2.2131	2.4844	2.702
				Aqos(0.1%)Br	2.0865	2.3406	2.5286
				Aqos(2.5%)	2.3092	2.5406	2.8317
				Aqos(2.5%)Br	2.1052	2.3156	2.6004
				Aqos(5.0%)	1.1709	1.4094	1.5692
				Aqos(5.0%)Br	1.1677	1.3906	1.5567

	Cb	SS	WW		5min	10min	20min
Greenturf	41.451	70	6/16/2003 0:00	Date(ADMD)	6/19/2003 18:30	6/19/2003 18:35	6/19/2003 18:40
2003F			6/22/2003 23:55	M/C (ADMD)	0.170357083	0.161528414	0.157616308
				Ac	0.977950622	1.032900498	1.168490509
				Bc	4.762642062	5.361643179	6.245022252
				Date(Vdmax)	6/22/2003 11:55	6/22/2003 11:55	6/22/2003 11:35
				M/C (Vdmax)	0.16570822	0.151276895	0.138629259
				Avdmax	0.585395552	0.719648582	0.65899479
				Bvdmax	2.947293123	4.037512662	4.09465385
				Aqos(0.1%)	1.978	2.0329	
				Aqos(0.1%)Br	1.8233	1.8657	1.981
				Aqos(2.5%)	2.103	2.0329	2.249
				Aqos(2.5%)Br	1.878	1.8524	2.0279
				Aqos(5.0%)	0.6467	0.9204	1.0622
				Aqos(5.0%)Br	0.6405	0.8954	1.0185

Lotus Park	52.717	54-72	7/30/2000 0:00	Date(ADMD)	8/2/2000 6:35	8/2/2000 6:40	8/2/2000 6:50
2000S			8/5/2000 23:55	M/C (ADMD)	0.190372123	0.18437087	0.179269337
				Ac	1.516335624	1.66344918	2.095643174
				Bc	6.448778178	7.35885016	9.594271044
				Date(Vdmax)	8/2/2000 17:25	8/2/2000 17:25	8/2/2000 17:35
				M/C (Vdmax)	0.182048065	0.170669434	0.165009561
				Avdmax	0.972813113	1.066531439	1.225921088
				Bvdmax	4.370902654	5.182574867	6.203473192
				Aqos(0.1%)	2.4101	2.6009	2.9456
				Aqos(0.1%)Br	2.2413	2.4572	2.7831
				Aqos(2.5%)	2.6038	2.7634	3.0456
				Aqos(2.5%)Br	2.3351	2.4822	2.7581
				Aqos(5.0%)	1.1601	1.4509	1.7206
				Aqos(5.0%)Br	1.1413	1.4009	1.6456

Orient Hills	45.472	55-62	9/17/1999 0:00	Date(ADMD)	9/20/1999 6:30	9/20/1999 6:35	9/20/1999 6:35
1999S			9/23/1999 23:55	M/C (ADMD)	0.163882489	0.156650814	0.148350332
				Ac	1.086805205	1.191294053	1.396378689
				Bc	5.544807553	6.413480036	8.016331552
				Date(Vdmax)	9/17/1999 6:25	9/17/1999 6:30	9/20/1999 6:00
				M/C (Vdmax)	0.144588447	0.142493573	0.122669072
				Avdmax	0.676145213	0.858373256	0.798377403
				Bvdmax	4.000198085	5.165570407	5.710006396
				Aqos(0.1%)	1.9931	2.1663	2.312
				Aqos(0.1%)Br	1.8493		2.1526
				Aqos(2.5%)	2.0743	2.2163	2.2839
				Aqos(2.5%)Br	1.8431	2.0163	2.0589
				Aqos(5.0%)	1.0868	1.1913	1.3964
				Aqos(5.0%)Br	1.0306	1.1788	1.3964

CLAREMONT	69.700	54-58	6/5/1998 0:00	Date(ADMD)	6/8/1998 19:40	6/8/1998 19:10	6/8/1998 19:25
1998F			6/11/1998 23:55	M/C (ADMD)	0.241426558	0.236655371	0.230587679
				Ac	1.37787874	1.341358311	1.452459419
				Bc	4.329358908	4.326623394	4.846486919
				Date(Vdmax)	6/9/1998 20:20	6/9/1998 20:25	6/9/1998 20:25
				M/C (Vdmax)	0.225588976	0.222868574	0.22219407
				Avdmax	0.960177886	0.986678785	1.127604137
				Bvdmax	3.296137755	3.440498931	3.94725738
				Aqos(0.1%)	2.0654	2.1414	2.1845
				Aqos(0.1%)Br	1.956	2.0289	2.0587
				Aqos(2.5%)	2.1716	2.1851	2.1025
				Aqos(2.5%)Br	2.0146	2.0164	1.9724
				Aqos(5.0%)	1.2654	1.257	1.3087
				Aqos(5.0%)Br	1.2279	1.1414	1.29

Westridge	63.837	60-67	7/11/2002 0:00	Date(ADMD)	7/14/2002 11:20	7/14/2002 11:25	7/14/2002 12:05
2002S			7/17/2002 23:55	M/C (ADMD)	0.192945243	0.17913367	0.175455682
				Ac	1.277326403	1.36188562	1.588622544
				Bc	5.342823362	6.240736623	7.465644166
				Date(Vdmax)	7/14/2002 11:20	7/14/2002 11:25	7/14/2002 12:00
				M/C (Vdmax)	0.192945243	0.17913367	0.175305442
				Avdmax	1.277326403	1.36188562	1.380682968
				Bvdmax	5.342823362	6.240736623	6.495187594
				Aqos(0.1%)	4.8773	4.5869	4.2324
				Aqos(0.1%)Br	4.1023	4.0619	3.7011
				Aqos(2.5%)	5.5023	5.0119	4.4136
				Aqos(2.5%)Br	4.3398	4.1619	3.7449
				Aqos(5.0%)	1.2773	1.3619	1.3886
				Aqos(5.0%)Br	1.2711	1.3619	1.3886

Tafelsig	48.564	56-63	6/10/1999 0:00	Date(ADMD)	6/13/1999 11:00	6/13/1999 11:05	6/13/1999 11:15
1999F			6/16/1999 23:55	M/C (ADMD)	0.184171958	0.180530878	0.178521094
				Ac	1.043049965	1.209840549	1.117166749
				Bc	4.620407049	5.491730742	5.14073098
				Date(Vdmax)	6/13/1999 12:20	6/13/1999 11:15	6/13/1999 11:15
				M/C (Vdmax)	0.173902414	0.17651131	0.178521094
				Avdmax	0.692867487	0.880709475	1.117166749
				Bvdmax	3.29136408	4.108826179	5.14073098
				Aqos(0.1%)	3.5555	4.3098	5.1922
				Aqos(0.1%)Br	3.1555	3.7223	4.4797
				Aqos(2.5%)	3.293	4.0098	4.9297
				Aqos(2.5%)Br	2.793	3.3598	3.9672
				Aqos(5.0%)	0.8618	0.9598	1.1172
				Aqos(5.0%)Br	0.843	0.9473	1.1172

HELDERBERG	66.761	61	8/10/1997 0:00	Date(ADMD)	8/13/1997 19:15	8/13/1997 19:20	8/13/1997 19:20
1997S			8/16/1997 23:55	M/C (ADMD)	0.275945195	0.269494608	0.242873895
				Ac	2.919997947	2.811831872	3.972453065
				Bc	7.661805989	7.621890308	12.38357838
				Date(Vdmax)	8/13/1997 19:30	8/13/1997 19:30	8/13/1997 19:40
				M/C (Vdmax)	0.258322262	0.259561574	0.242704955
				Avdmax	1.646520063	2.15359233	1.970544192
				Bvdmax	4.727379159	6.143446016	6.1485492
				Aqos(0.1%)	5.6075	6.0147	6.9415
				Aqos(0.1%)Br	4.72	5.0272	5.779
				Aqos(2.5%)	7.62	8.4647	9.6915
				Aqos(2.5%)Br	5.6075	6.3459	7.3415
				Aqos(5.0%)	2.2075	2.4147	2.754
				Aqos(5.0%)Br	2.12	2.2897	2.679

	Cb	SS	WW		5min	10min	20min
Walmer Dunes	26.676	43-54	6/5/1998 0:00	Date(ADMD)	6/8/1998 13:55	6/8/1998 18:55	6/8/1998 18:55
1998F			6/11/1998 23:55	M/C (ADMD)	0.131882314	0.131514387	0.127822797
				Ac	0.461023548	0.553338757	0.638615114
				Bc	3.034695745	3.654100222	4.357482065
				Date(Vdmax)	6/8/1998 13:55	6/8/1998 18:55	6/8/1998 18:55
				M/C (Vdmax)	0.131882314	0.131514387	0.127822797
				Avdmax	0.461023548	0.553338757	0.638615114
				Bvdmax	3.034695745	3.654100222	4.357482065
				Aqos(0.1%)	1.3501	1.708	2.0074
				Aqos(0.1%)Br	1.261	1.5877	1.8652
				Aqos(2.5%)	1.2641	1.682	1.7761
				Aqos(2.5%)Br	1.147	1.5033	1.6136
				Aqos(5.0%)	0.461	0.5533	0.6386
				Aqos(5.0%)Br	0.461	0.5533	0.6386

Ikgomotseng	23.191	31-59	8/8/2003 0:00	Date(ADMD)	8/11/2003 7:00	8/11/2003 7:05	8/11/2003 7:15
2003S			8/14/2003 23:55	M/C (ADMD)	0.066971197	0.061164579	0.061694192
				Ac	0.220577173	0.308040948	0.441597494
				Bc	3.073035338	4.728222774	6.716248037
				Date(Vdmax)	8/11/2003 17:45	8/11/2003 17:50	8/11/2003 18:00
				M/C (Vdmax)	0.054966834	0.055662859	0.051960219
				Avdmax	0.070402133	0.093512192	0.13211897
				Bvdmax	1.210409007	1.586462466	2.410575681
				Aqos(0.1%)	0.6362	0.6643	0.8037
				Aqos(0.1%)Br	0.6018	0.6268	0.7572
				Aqos(2.5%)	0.5979	0.6205	0.7885
				Aqos(2.5%)Br	0.5456	0.5643	0.7353
				Aqos(5.0%)	0.1393	0.1299	0.2291
				Aqos(5.0%)Br	0.1331	0.1268	0.2228

Macongo	32.154	30-39	1/25/2003 0:00	Date(ADMD)	1/28/2003 20:15	1/28/2003 20:20	1/28/2003 20:30
2003F			1/31/2003 23:55	M/C (ADMD)	0.126163671	0.118385565	0.11511895
				Ac	0.39007465	0.395322849	0.401881542
				Bc	2.701739718	2.943959694	3.089129642
				Date(Vdmax)	1/28/2003 19:35	1/25/2003 20:45	1/25/2003 20:50
				M/C (Vdmax)	0.117996379	0.104214613	0.102421809
				Avdmax	0.28064229	0.245170143	0.255144679
				Bvdmax	2.097755198	2.107380383	2.235972034
				Aqos(0.1%)	0.7526	0.6883	0.6706
				Aqos(0.1%)Br	0.6994	0.6438	0.6269
				Aqos(2.5%)	0.7026	0.5891	0.5644
				Aqos(2.5%)Br	0.6494	0.5578	0.5433
				Aqos(5.0%)	0.3557	0.3828	0.38
				Aqos(5.0%)Br	0.3526	0.3703	0.3706

Mafefe	21.844	34-64	4/24/2001 0:00	Date(ADMD)	4/27/2001 18:35	4/27/2001 18:35	4/30/2001 19:00
2001F			4/30/2001 23:55	M/C (ADMD)	0.110436503	0.104273842	0.100742946
				Ac	0.360846166	0.459839795	0.570078026
				Bc	2.906607578	3.950084959	5.088660859
				Date(Vdmax)	4/27/2001 18:35	4/27/2001 18:35	4/27/2001 18:35
				M/C (Vdmax)	0.110436503	0.104273842	0.09822223
				Avdmax	0.360846166	0.459839795	0.507123345
				Bvdmax	2.906607578	3.950084959	4.655896717
				Aqos(0.1%)	1.4233	1.4661	1.4146
				Aqos(0.1%)Br	1.3421	1.3848	1.3451
				Aqos(2.5%)	1.1858	1.0723	1.0545
				Aqos(2.5%)Br	1.0983	1.0348	1.0201
				Aqos(5.0%)	0.3608	0.4598	0.5576
				Aqos(5.0%)Br	0.3608	0.4598	0.5451

Makipsvlei	49.267	90-98	5/30/1997 0:00	Date(ADMD)	6/2/1997 18:30	6/2/1997 18:30	6/2/1997 18:35
1997F			6/5/1997 23:55	M/C (ADMD)	0.115967111	0.112258122	0.106622035
				Ac	0.737910437	0.859202346	0.888463544
				Bc	5.625190523	6.794607758	7.444368825
				Date(Vdmax)	6/4/1997 7:15	6/4/1997 7:15	6/4/1997 7:15
				M/C (Vdmax)	0.099753723	0.097801774	0.099857861
				Avdmax	0.344582245	0.416019498	0.557394393
				Bvdmax	3.109747417	3.837681447	5.024483578
				Aqos(0.1%)	1.2535	1.2576	1.2002
				Aqos(0.1%)Br	1.1942	1.1905	1.1603
				Aqos(2.5%)	1.1543	1.1623	1.1135
				Aqos(2.5%)Br	1.1004	1.1217	1.076
				Aqos(5.0%)	0.5754	0.6717	0.701
				Aqos(5.0%)Br	0.5567	0.6467	0.6885

Mfazazane	65.240	58-64	6/1/2002 0:00	Date(ADMD)	6/4/2002 18:10	6/4/2002 18:10	6/4/2002 18:10
2002F			6/7/2002 23:55	M/C (ADMD)	0.067840617	0.062063032	0.061930453
				Ac	0.300455943	0.28553471	0.257829064
				Bc	4.128394429	4.315186553	3.90537421
				Date(Vdmax)	6/5/2002 18:10	6/5/2002 18:15	6/5/2002 18:25
				M/C (Vdmax)	0.059723952	0.05874703	0.057107231
				Avdmax	0.163024634	0.173632883	0.17892952
				Bvdmax	2.566611116	2.781969851	2.954290481
				Aqos(0.1%)	0.5403	0.4676	0.486
				Aqos(0.1%)Br	0.5208	0.4558	0.4689
				Aqos(2.5%)	0.4887	0.419	0.4516
				Aqos(2.5%)Br	0.463	0.4058	0.436
				Aqos(5.0%)	0.2458	0.2074	0.2313
				Aqos(5.0%)Br	0.2395	0.2043	0.2281

Qumbu	38.549	40-42	5/24/2000 0:00	Date(ADMD)	5/27/2000 18:25	5/27/2000 18:25	5/27/2000 18:40
2000F			5/30/2000 23:55	M/C (ADMD)	0.063476417	0.059582177	0.058809351
				Ac	0.468745591	0.468544215	0.462493944
				Bc	6.915817221	7.39528749	7.401798608
				Date(Vdmax)	5/27/2000 18:40	5/27/2000 18:45	5/27/2000 18:55
				M/C (Vdmax)	0.061194225	0.059431472	0.05847814
				Avdmax	0.393209343	0.40190411	0.408516996
				Bvdmax	6.03238621	6.360575408	6.577289973
				Aqos(0.1%)	0.9281	0.8935	0.9187
				Aqos(0.1%)Br	0.8687	0.8486	0.8719
				Aqos(2.5%)	0.8937	0.823	0.823
				Aqos(2.5%)Br	0.8344	0.7748	0.775
				Aqos(5.0%)	0.4437	0.4029	0.4187
				Aqos(5.0%)Br	0.4375	0.406	0.4125

ANTIOCH	39.253	46-56	1/6/2003 0:00	Date(ADMD)	1/9/2003 19:45	1/9/2003 19:50	1/9/2003 20:15
2003F			1/12/2003 23:55	M/C (ADMD)	0.070073721	0.068476439	0.066295498
				Ac	0.123353408	0.15070786	0.168568498
				Bc	1.636984215	2.050163894	2.374115459
				Date(Vdmax)	1/9/2003 17:35	1/9/2003 17:40	1/9/2003 17:45
				M/C (Vdmax)	0.062020497	0.05864616	0.057817477
				Avdmax	0.080500026	0.087747974	0.096013427
				Bvdmax	1.217458396	1.408479116	1.564616399
				Aqos(0.1%)	0.3109	0.2976	0.2744
				Aqos(0.1%)Br	0.2939	0.2796	0.2594
				Aqos(2.5%)	0.3085	0.2894	0.2686
				Aqos(2.5%)Br	0.2839	0.2695	0.2514
				Aqos(5.0%)	0.123	0.1476	0.1514
				Aqos(5.0%)Br	0.1202	0.1429	0.1483

GASESE	79.119	57-74	8/2/2002 0:00	Date(ADMD)	8/5/2002 6:50	8/5/2002 6:50	8/5/2002 7:05
2002S			8/8/2002 23:55	M/C (ADMD)	0.045122727	0.031095661	0.028410675
				Ac	0.506507919	0.566595692	0.600462247
				Bc	10.71860966	17.65445767	20.53463012
				Date(Vdmax)	8/5/2002 6:50	8/4/2002 15:20	8/5/2002 7:05
				M/C (Vdmax)	0.045122727	0.017763231	0.028410675
				Avdmax	0.506507919	0.09626724	0.600462247
				Bvdmax	10.71860966	5.323199461	20.53463012
				Aqos(0.1%)	2.1378		1.5161
				Aqos(0.1%)Br	1.9128	1.4791	1.4036
				Aqos(2.5%)	2.169	1.6291	1.4255
				Aqos(2.5%)Br	1.8565	1.4416	1.2973
				Aqos(5.0%)	0.5034	0.4853	0.6005
				Aqos(5.0%)Br	0.5034	0.4353	0.6005

GARAGAPOLA	26.012	55-59	6/2/2002 0:00	Date(ADMD)	6/5/2002 18:20	6/5/2002 18:25	6/5/2002 18:35
2002F			6/8/2002 23:55	M/C (ADMD)	0.097771042	0.097609122	0.095008301
				Ac	0.560218507	0.591053825	0.647489964
				Bc	5.16968369	5.464259595	6.167598354
				Date(Vdmax)	6/5/2002 6:55	6/5/2002 6:55	6/5/2002 18:35
				M/C (Vdmax)	0.093329806	0.08634737	0.095008301
				Avdmax	0.303361033	0.363135453	0.647489964
				Bvdmax	2.947058588	3.842382929	6.167598354
				Aqos(0.1%)	1.0337	1.1411	1.1412
				Aqos(0.1%)Br	0.9698	1.0442	1.085
				Aqos(2.5%)	1.004	1.1493	1.1725
				Aqos(2.5%)Br	0.9321	1.0286	1.0537
				Aqos(5.0%)	0.354	0.5473	0.6475
				Aqos(5.0%)Br	0.5602	0.5348	0.6475

Tambo	52.399	63	4/19/2003 0:00	Date(ADMD)	4/22/2003 18:25	4/22/2003 18:20	4/22/2003 18:20
2003F			4/25/2003 23:55	M/C (ADMD)	0.045789678	0.044549045	0.044450745
				Ac	0.500225436	0.531023328	0.597338539
				Bc	10.42418939	11.38894782	12.84087346
				Date(Vdmax)	4/22/2003 15:35	4/22/2003 15:30	4/22/2003 15:20
				M/C (Vdmax)	0.034007374	0.031220304	0.029516497
				Avdmax	0.082016977	0.106261884	0.107727267
				Bvdmax	2.329724013	3.2973528	3.542003516
				Aqos(0.1%)	0.8502	0.8685	0.9473
				Aqos(0.1%)Br			
				Aqos(2.5%)	0.5065	0.481	0.4973
				Aqos(2.5%)Br			
				Aqos(5.0%)	0.2018	0.306	0.363
				Aqos(5.0%)Br			

	Cb	SS	WW		5min	10min	20min
Vlaklaagte	89.620	63-71	6/22/2005 0:00	Date(ADMD)	6/25/2005 18:40	6/25/2005 18:45	6/25/2005 18:55
2005F			6/28/2005 23:55	M/C (ADMD)	0.044394683	0.042217308	0.037669106
				Ac	0.070148578	0.07536441	0.138321951
				Bc	1.509963564	1.709789908	3.533704408
				Date(Vdmax)	6/25/2005 18:05	6/25/2005 18:45	6/25/2005 18:55
				M/C (Vdmax)	0.04327362	0.042217308	0.037669106
				Avdmax	0.064903337	0.07536441	0.138321951
				Bvdmax	1.434932758	1.709789908	3.533704408
				Aqos(0.1%)	1.5576	1.5129	1.1586
				Aqos(0.1%)Br	1.3951	1.3941	1.1024
				Aqos(2.5%)	1.6119	1.5316	1.1508
				Aqos(2.5%)Br	1.3616	1.3301	1.0352
				Aqos(5.0%)	0.0701	0.0754	0.1383
				Aqos(5.0%)Br	1.3616	1.3301	1.0352

Umlazi AA	45.965	34-56	7/4/1998 0:00	Date(ADMD)	7/7/1998 17:55	7/7/1998 17:55	7/10/1998 18:15
1998S			7/10/1998 23:55	M/C (ADMD)	0.185312304	0.175579246	0.170385703
				Ac	1.34597762	1.560247073	1.401821387
				Bc	5.91731571	7.326037105	6.825520229
				Date(Vdmax)	7/10/1998 18:35	7/9/1998 15:10	7/10/1998 18:35
				M/C (Vdmax)	0.171895004	0.133802475	0.16560939
				Avdmax	0.921324538	0.518024898	1.135450934
				Bvdmax	4.438485338	3.353539493	5.720748084
				Aqos(0.1%)	1.8804	1.8337	1.8831
				Aqos(0.1%)Br	1.771	1.729	1.819
				Aqos(2.5%)	1.921	1.8352	1.8643
				Aqos(2.5%)Br	1.7706	1.7134	1.7476
				Aqos(5.0%)	1.2335	1.2415	1.2706
				Aqos(5.0%)Br	1.196	1.2102	1.2518

Sweetwaters	52.752	51-53	2/1/1997 0:00	Date(ADMD)	2/4/1997 19:45	2/4/1997 19:45	2/4/1997 20:00
1997F			2/7/1997 23:55	M/C (ADMD)	0.101453723	0.098701435	0.09850409
				Ac	0.268086745	0.263751036	0.260943341
				Bc	2.374366762	2.408459711	2.388117635
				Date(Vdmax)	2/4/1997 6:25	2/6/1997 6:05	2/6/1997 19:40
				M/C (Vdmax)	0.085786964	0.081637609	0.094309936
				Avdmax	0.15650069	0.144598917	0.227239323
				Bvdmax	1.667793844	1.626630272	2.182255715
				Aqos(0.1%)	0.2952	0.2778	0.279
				Aqos(0.1%)Br	0.2873	0.2716	0.2729
				Aqos(2.5%)	0.3025	0.2856	0.2877
				Aqos(2.5%)Br	0.2931	0.277	0.2785
				Aqos(5.0%)	0.2681	0.2575	0.2609
				Aqos(5.0%)Br	0.2681	0.2575	0.2609

Umgaga	54.791	45-67	5/8/1998 0:00	Date(ADMD)	5/11/1998 19:05	5/11/1998 19:05	5/11/1998 19:05
1998F			5/14/1998 23:55	M/C (ADMD)	0.067171399	0.06307687	0.06307687
				Ac	0.55199416	0.583208143	0.583208143
				Bc	7.665702244	8.662782379	8.662782379
				Date(Vdmax)	5/11/1998 19:05	5/11/1998 19:05	5/11/1998 19:15
				M/C (Vdmax)	0.067171399	0.06307687	0.060596141
				Avdmax	0.55199416	0.583208143	0.612529794
				Bvdmax	7.665702244	8.662782379	9.495866351
				Aqos(0.1%)	1.727	1.6457	1.8996
				Aqos(0.1%)Br	1.627	1.5707	1.7933
				Aqos(2.5%)	1.6989	1.5582	1.7496
				Aqos(2.5%)Br	1.5457	1.4457	1.6371
				Aqos(5.0%)	0.552	0.5832	
				Aqos(5.0%)Br	0.552	0.5832	0.6871

Peacetown	42.726	36-65	5/6/2006 0:00	Date(ADMD)	5/10/2006 6:35	5/9/2006 19:35	5/9/2006 19:45
2006F			5/12/2006 23:55	M/C (ADMD)	0.097562082	0.096623446	0.093147688
				Ac	0.796048368	0.569219708	0.573828862
			Edited	Bc	7.363354902	5.321894039	5.586590929
			5/11/2006 10:20	Date(Vdmax)	5/12/2006 6:55	5/9/2006 19:35	5/9/2006 19:45
				M/C (Vdmax)	0.09109771	0.096623446	0.093147688
				Avdmax	0.402893062	0.569219708	0.573828862
				Bvdmax	4.01975449	5.321894039	5.586590929
				Aqos(0.1%)	0.9203	0.9473	0.9324
				Aqos(0.1%)Br	0.882	0.9169	0.8973
				Aqos(2.5%)	0.896	0.9485	0.8754
				Aqos(2.5%)Br	0.8523	0.9005	0.8431
				Aqos(5.0%)	0.5085	0.5692	0.5738
				Aqos(5.0%)Br	0.5023	0.5692	0.5738

Ongwediva	34.705	46-53	5/4/2001 0:00	Date(ADMD)	5/7/2001 18:45	5/7/2001 18:45	5/7/2001 18:50
2001F			5/10/2001 23:55	M/C (ADMD)	0.140656695	0.138815298	0.131425384
				Ac	1.067474884	1.080389996	1.185427315
				Bc	6.521747124	6.702541776	7.834347109
				Date(Vdmax)	5/7/2001 18:40	5/7/2001 18:45	5/7/2001 18:55
				M/C (Vdmax)	0.136973902	0.138815298	0.129773047
				Avdmax	0.913068604	1.080389996	1.089613217
				Bvdmax	5.752935593	6.702541776	7.306685103
				Aqos(0.1%)	2.9175	3.1991	3.2354
				Aqos(0.1%)Br	2.5925	2.8804	2.9229
				Aqos(2.5%)	2.8675	3.171	2.8042
				Aqos(2.5%)Br	2.5425	2.7991	2.5542
				Aqos(5.0%)	1.005	1.0804	1.1417
				Aqos(5.0%)Br	1.005	1.0804	1.1354

Matshana	41.741	43-54	7/10/2006 0:00	Date(ADMD)	7/13/2006 18:15	7/13/2006 18:15	7/13/2006 18:20
2006S			7/16/2006 23:55	M/C (ADMD)	0.128262735	0.127016957	0.121880565
				Ac	0.728687816	0.870898349	1.009769983
				Bc	4.952524401	5.985653463	7.275143875
				Date(Vdmax)	7/11/2006 19:10	7/11/2006 19:15	7/11/2006 19:25
				M/C (Vdmax)	0.107358694	0.103605834	0.102582992
				Avdmax	0.293878264	0.337966068	0.402484587
				Bvdmax	2.4434712	2.924070974	3.521017537
				Aqos(0.1%)	1.4224	1.5756	1.5426
				Aqos(0.1%)Br	1.3459	1.474	1.4691
				Aqos(2.5%)	1.3474	1.5623	1.4348
				Aqos(2.5%)Br	1.2615	1.4459	1.3535
				Aqos(5.0%)	0.5474	0.6896	0.7348
				Aqos(5.0%)Br	0.5224	0.6459	0.6973

La Lucia	77.211	53-60	12/2/2005 0:00	Date(ADMD)	12/5/2005 19:55	12/5/2005 19:55	12/5/2005 20:00
2005S			12/8/2005 23:55	M/C (ADMD)	0.215723461	0.211913034	0.205715284
				Ac	0.978561149	0.980570712	1.082089863
			Edited	Bc	3.557622097	3.646661012	4.178043679
			0:00 of each day	Date(Vdmax)	12/5/2005 20:40	12/5/2005 20:25	12/5/2005 20:25
				M/C (Vdmax)	0.20469323	0.202740676	0.20260636
				Avdmax	0.822284437	0.85586139	0.94238487
				Bvdmax	3.194870588	3.365597305	3.708924549
				Aqos(0.1%)	2.1786	2.2306	2.2727
				Aqos(0.1%)Br	2.0379	2.0556	2.1227
				Aqos(2.5%)	2.1286	2.1577	2.1133
				Aqos(2.5%)Br	1.9036	1.9306	1.9208
				Aqos(5.0%)	0.9778	0.9806	1.0008
				Aqos(5.0%)Br	0.977	0.9806	0.9946

Kwazekhele	38.002	63	8/19/1995 0:00	Date(ADMD)	8/22/1995 19:10	8/22/1995 19:15	8/22/1995 19:20
1995S			8/25/1995 23:55	M/C (ADMD)	0.111525459	0.108876893	0.107645024
				Ac	0.54122366	0.64171455	0.666366208
			Edited	Bc	4.311692114	5.25223165	5.524038004
			0:00 of each day	Date(Vdmax)	8/22/1995 18:20	8/22/1995 18:25	8/22/1995 19:00
				M/C (Vdmax)	0.102007161	0.098710134	0.103210838
				Avdmax	0.392382438	0.412654954	0.555957351
				Bvdmax	3.454234139	3.767817068	4.8306606
				Aqos(0.1%)	1.477	1.7417	1.8664
				Aqos(0.1%)Br	1.3725	1.6042	1.7414
				Aqos(2.5%)	1.367	1.5417	1.7601
				Aqos(2.5%)Br	1.2412	1.4136	1.6164
				Aqos(5.0%)	0.535	0.5792	0.6476
				Aqos(5.0%)Br	0.5162	0.5667	0.6289

Khayalitsha	49.439	74-88	8/8/2005 0:00	Date(ADMD)	8/11/2005 19:20	8/11/2005 19:10	8/11/2005 19:20
2005S			8/14/2005 23:55	M/C (ADMD)	0.120782222	0.118130308	0.116967949
				Ac	1.102324478	1.038729523	1.178500201
				Bc	8.024221303	7.754352764	8.896911185
				Date(Vdmax)	8/11/2005 18:50	8/11/2005 19:10	8/11/2005 19:20
				M/C (Vdmax)	0.105613621	0.118130308	0.116967949
				Avdmax	0.611366524	1.038729523	1.178500201
				Bvdmax	5.177342516	7.754352764	8.896911185
				Aqos(0.1%)	1.8554	2.0903	2.3285
				Aqos(0.1%)Br	1.7398	1.9512	2.166
				Aqos(2.5%)	1.7523	1.8887	2.066
				Aqos(2.5%)Br	1.6273	1.7387	1.8723
				Aqos(5.0%)	0.9586	1.0387	1.1785
				Aqos(5.0%)Br	0.9461	1.0387	1.1785

Kabega	61.493	30-37	4/7/2005 0:00	Date(ADMD)	4/10/2005 12:25	4/10/2005 12:25	4/10/2005 12:35
2005F			4/13/2005 23:55	M/C (ADMD)	0.128417165	0.122434942	0.106991633
				Ac	0.336411089	0.337727522	0.406738151
				Bc	2.283262748	2.420696799	3.394850247
				Date(Vdmax)	4/10/2005 12:25	4/10/2005 12:25	4/11/2005 19:15
				M/C (Vdmax)	0.128417165	0.122434942	0.095414442
				Avdmax	0.336411089	0.337727522	0.211271959
				Bvdmax	2.283262748	2.420696799	2.002983595
				Aqos(0.1%)	1.1989	1.2643	1.1114
				Aqos(0.1%)Br	1.0989	1.1565	1.0364
				Aqos(2.5%)	1.1427	1.0846	0.8255
				Aqos(2.5%)Br	1.0098	0.969	0.7692
				Aqos(5.0%)	0.3356	0.3377	0.313
				Aqos(5.0%)Br	0.3348	0.3377	0.3067

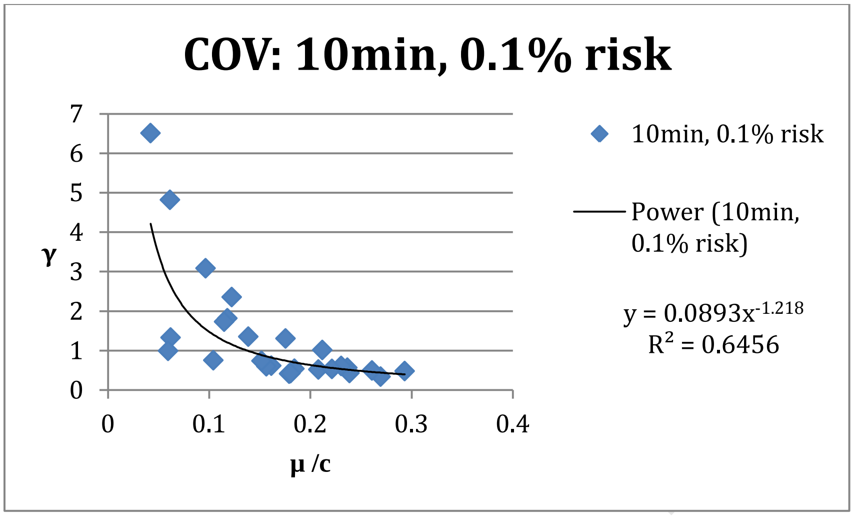
CLOETESVILLE	54.000	47-71	7/21/1994 0:00	Date(ADMD)	7/24/1994 11:40	7/24/1994 11:40	7/24/1994 11:55
1994S			7/27/1994 23:55	M/C (ADMD)	0.26848713	0.260982361	0.261869266
				Ac	2.719324501	2.688758715	2.839062425
				Bc	7.408998964	7.613695094	8.002463436
				Date(Vdmax)	7/24/1994 12:30	7/24/1994 12:35	7/24/1994 12:40
				M/C (Vdmax)	0.23374137	0.235165563	0.240504585
				Avdmax	1.092972945	1.214365528	1.42014426
				Bvdmax	3.583019776	3.949509282	4.48470891
				Aqos(0.1%)	6.2693	6.0325	6.1953
				Aqos(0.1%)Br	5.3756	5.2388	5.3734
				Aqos(2.5%)	8.0193	7.6356	7.5766
				Aqos(2.5%)Br	6.2193	6.1263	6.0547
				Aqos(5.0%)	1.9568	1.8888	2.0516
				Aqos(5.0%)Br	1.8318	1.8013	1.9641

DRIEKOPPIES	29.453	33-71	7/30/2005 0:00	Date(ADMD)	8/2/2005 18:35	8/2/2005 18:35	8/2/2005 18:45
2005S			8/5/2005 23:55	M/C (ADMD)	0.105847787	0.114934089	0.139293913
				Ac	0.669159447	0.687335095	0.752175342
				Bc	5.652743571	5.292919335	4.647740038
				Date(Vdmax)	8/2/2005 18:15	8/2/2005 18:15	8/2/2005 18:45
				M/C (Vdmax)	0.091109048	0.097054872	0.139293913
				Avdmax	0.34613328	0.412970499	0.752175342
				Bvdmax	3.452976559	3.842050283	4.647740038
				Aqos(0.1%)	2.0942	2.7217	2.6522
				Aqos(0.1%)Br	1.8754	2.3901	2.3772
				Aqos(2.5%)	1.9442	2.4936	2.6522
				Aqos(2.5%)Br	1.6754	2.1498	2.2522
				Aqos(5.0%)	0.6692	0.6873	0.7522
				Aqos(5.0%)Br	0.5567	0.6873	0.7522

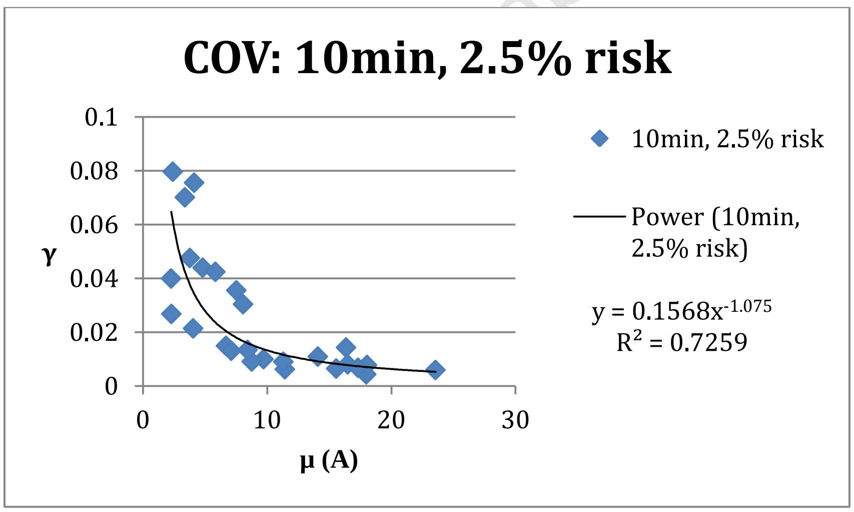
DINOKANA	39.253	47-68	6/21/2006 0:00	Date(ADMD)	6/24/2006 19:05	6/24/2006 19:10	6/24/2006 19:20
2006F			6/27/2006 23:55	M/C (ADMD)	0.067807721	0.061415582	0.061415582
				Ac	0.078023441	0.091166241	0.094849737
				Bc	1.072633741	1.345125784	1.449542314
				Date(Vdmax)	6/24/2006 19:05	6/24/2006 19:10	6/24/2006 19:20
				M/C (Vdmax)	0.067807721	0.061415582	0.061415582
				Avdmax	0.078023441	0.091166241	0.094849737
				Bvdmax	1.072633741	1.345125784	1.449542314
				Aqos(0.1%)	1.0905	0.8677	0.9323
				Aqos(0.1%)Br	1.0186	0.8224	0.8698
				Aqos(2.5%)	1.1155	0.8724	0.9198
				Aqos(2.5%)Br	0.9905	0.813	0.8448
				Aqos(5.0%)	0.0779	0.0912	0.0948
				Aqos(5.0%)Br	0.0776	0.0912	0.0948

APPENDIX E

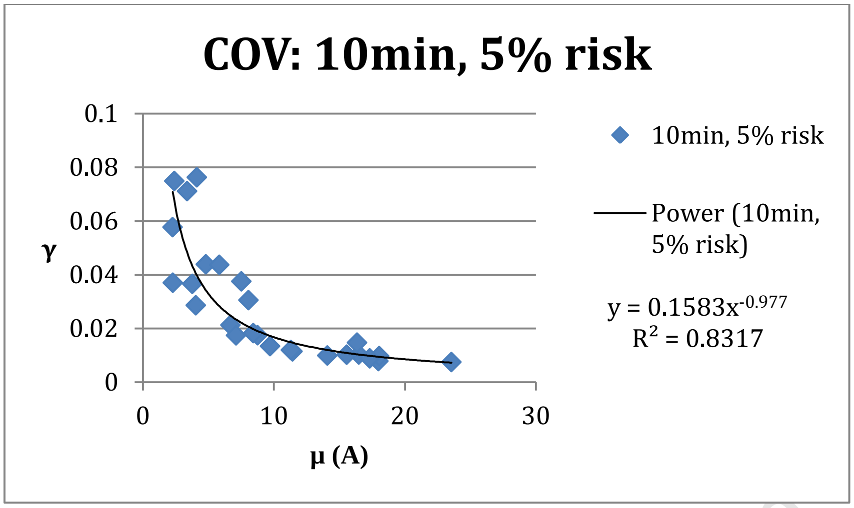
WITH GEYSERS



E1

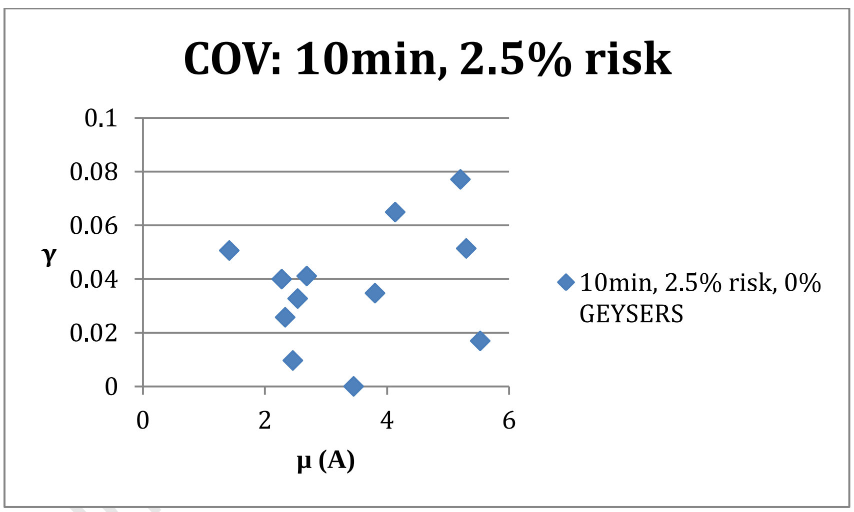


E2

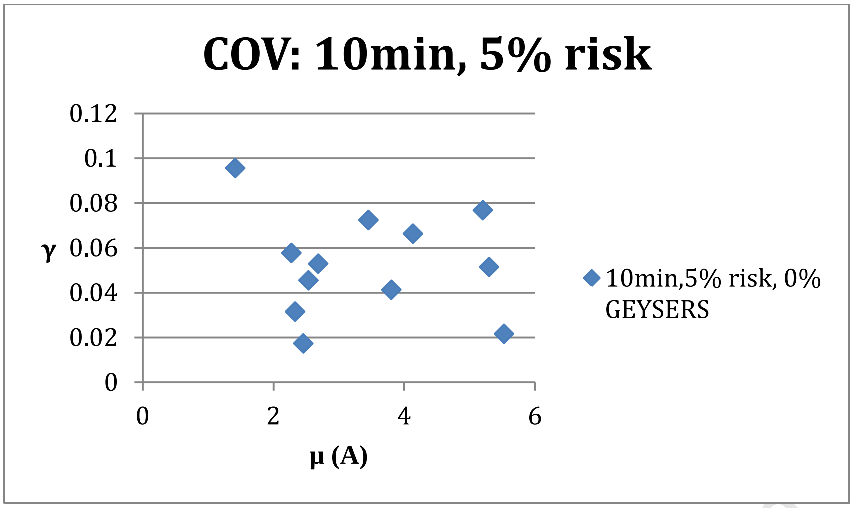


E3

WITHOUT GEYSERS

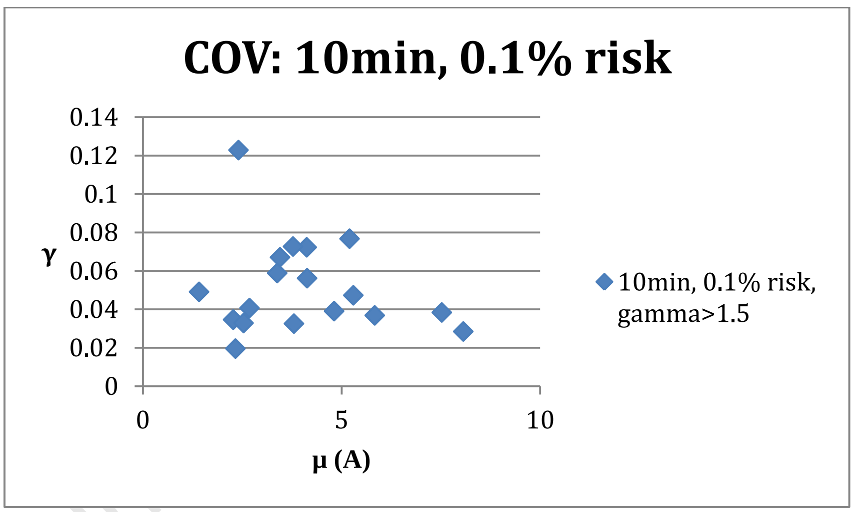


E4

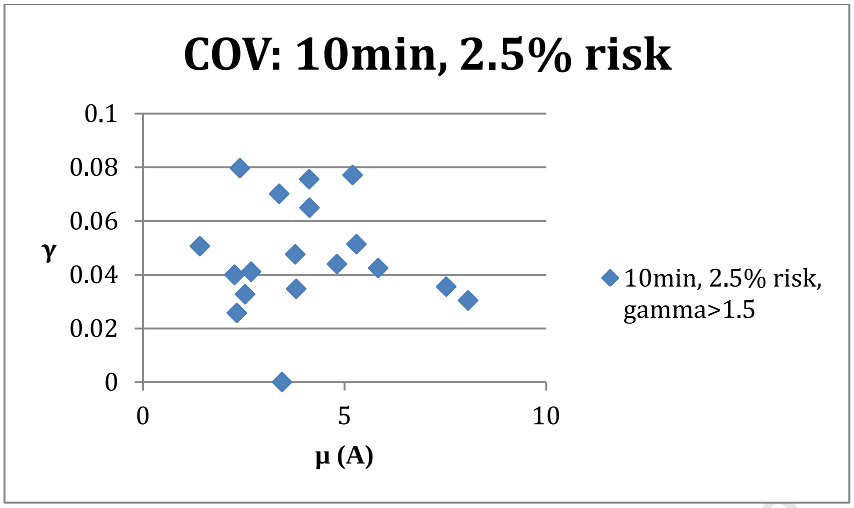


E5

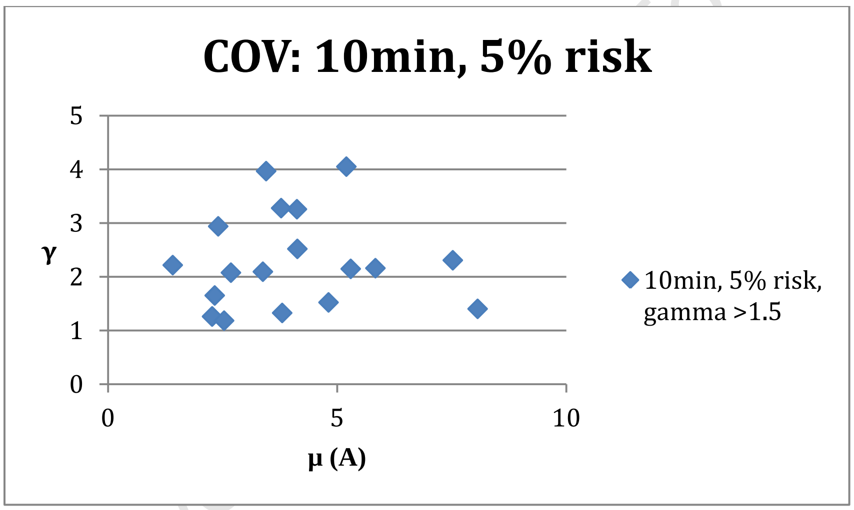
GAMMA> 1.5



E6


COV: 10min, 2.5% risk
0.1
0.08
0.06
0.04
0.02
0
γ
0
5
10
μ (A)
10min, 2.5% risk, gamma>1.5

E7


COV: 10min, 5% risk
5
4
3
2
1
0
γ
0
5
10
μ (A)
10min, 5% risk, gamma >1.5

E8

APPENDIX F

Community	5-10min_voltage difference (p.u.)	5-20min_voltage difference (p.u.)
ANTIOCH-2003-F	0.064894676	0.098077365
CLAREMONT-1998-F	0.01739112	0.055804472
CLOETESVILLE-1994-S	0.023820735	0.047545159
DINOKANA-2006-F	0.086873901	0.120100403
DRIEKOPPIES-2005-S	0.000867509	-0.137831907
GARAGAPOLA-2002-F	0.118600751	0.206389266
HELDERBERG-1997-S	0.065956931	0.096706007
Ikgomotseng-2003-S	0.063543788	0.203144603
Kabega-2005-F	0.040088332	0.106337595
Khayalitsha-2005-S	0.067052468	0.112148277
Kwazekhele-1995-S	0.044127544	0.096883512
La Lucia-2005-S	0.019087036	0.046165531
Lotus Park-2000-S	0.080153842	0.143882088
Maconqo-2003-F	0.061957314	0.086164785
Mafefe-2001-F	0.118805387	0.190823228
Makipsvlei-1997-F	0.074497938	0.142787715
Matshana-2006-S	0.070372967	0.127537858
Mfazazane-2002-F	0.034019661	0.066994349
Moreletta Park-2001-S	0.028644825	0.08508448
Ongwediva-2001-F	0.039821404	0.099347996
Peacetown-2006-F	0.058764157	0.09217907
Qumbu-2000-F	0.034386913	0.054353508
Rontree Estate-2000-F	0.04786584	0.085275879
Sanctuary Gardens-1999-S	0.065297364	0.123715512
Summerstrand-2000-F	0.091405514	0.13420881
Sweetwaters-1997-F	0.018376658	0.027881826
Tafelsig-1999-F	0.056286532	0.111959685
Umlazi AA-1998-S	0.041476116	0.091080917
Vlaklaagte-2005-F	0.060646158	0.300101415
Walmer Dunes-1998-F	0.056564076	0.120046934
Welgemoed-2002-F	0.036780945	0.055635823
Westridge-2002-S	0.080751019	0.101880837
Woodhaven-2002-S	0.028204903	0.048699587
GASESE-2002-S	0.229907638	0.400739265
Greenturf-2003-F	0.129972684	0.171698496
Orient Hills-1999-S	0.179827936	0.105663774
Tambo-2003-F	0.195662106	0.053961667
AVERAGE	6.85%	11.01%